REFINEMENT AND PERFORMANCE ANALYSIS OF THE STEPPED FREQUENCY MICROWAVE RADIOMETER IN EXTRA TROPICAL CYCLONE CONDITIONS

Jezabel Vilardell Sanchez
University of Massachusetts Amherst

Follow this and additional works at: https://scholarworks.umass.edu/dissertations_2

Part of the Electrical and Electronics Commons

Recommended Citation
https://doi.org/10.7275/35743704 https://scholarworks.umass.edu/dissertations_2/2913

This Open Access Dissertation is brought to you for free and open access by the Dissertations and Theses at ScholarWorks@UMass Amherst. It has been accepted for inclusion in Doctoral Dissertations by an authorized administrator of ScholarWorks@UMass Amherst. For more information, please contact scholarworks@library.umass.edu.
REFINEMENT AND PERFORMANCE ANALYSIS OF THE STEPPED FREQUENCY MICROWAVE RADIOMETER IN EXTRA TROPICAL CYCLONE CONDITIONS

A Dissertation Presented

by

JEZABEL VILARDELL SÁNCHEZ

Submitted to the Graduate School of the University of Massachusetts Amherst in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

September 2023

Electrical and Computer Engineering
REFINEMENT AND PERFORMANCE ANALYSIS OF
THE STEPPED FREQUENCY MICROWAVE
RADIOMETER IN EXTRA TROPICAL CYCLONE
CONDITIONS

A Dissertation Presented
by
JEZABEL VILARDELL SÁNCHEZ

Approved as to style and content by:

________________________
Stephen J. Frasier, Chair

________________________
Paul Siqueira, Member

________________________
Michael Zink, Member

________________________
Brian Van Koten, Member

Christopher Hollot, Department Head
Electrical and Computer Engineering
A mi niño, mi luz, mi ángel.
Dark and difficult times lie ahead, soon we must all face the choice between what is right and what is easy.

ALBUS P. W. B. DUMBLEDORE
J.K. ROWLING
ACKNOWLEDGMENTS

I would like to express my sincere gratitude and appreciation to the following individuals and organizations who have contributed to the completion of this dissertation.

First, I would like to extend my deepest gratitude to my advisor Professor Stephen Frasier. Steve, thank you for all your unwavering support, guidance, knowledge, insightful feedback and patience. This has been a long and sometimes exhausting journey, I doubted myself many times but you have always kept me going, told me to trust the process and to be patient, because if it were easy, it would have already been done. I am forever grateful to have you as my mentor and for the opportunity that you granted me.

I would also like to thank my other committee members Professor Paul Siqueira, Professor Michael Zink and Professor Brian Van Koten for their time, expertise and advice. Special thanks to Paul, for all his support and advice in helping me secure the job that, as cliché as it may sound, was truly my dream.

I would also like to acknowledge the people at NOAA/NESDIS/STAR, Dr. Paul Chang, Dr. Zorana Jelenak and Dr. Joe Sapp. Thank you for all your support and guidance in this project, your contributions have been vital to the success of this research. I feel incredibly fortunate to have had the opportunity to learn from you in this exhilarating and unforgettable experience of flying through hurricanes and winter storms. This has made a lasting impact, and I will forever cherish the experiences and knowledge gained. Thank you for sharing your passion with such enthusiasm.

My sincere appreciation to the dedicated individuals at NOAA AOC for their extraordinary efforts in ensuring the safety and readiness of the aircraft.
To my fellow MIRSL’ers, thank you to all of you that have showed support and for the good times in the lab, specially Marc. You have been part of my PhD journey almost since the beginning, thank you for being there through the ups and downs, there have been many, and for being a shoulder to lean on.

The PhD journey is a long a difficult path that I could have not done without the help and endless support of my friends.

Aida, I have no words to express how deeply thankful I am to have you as my friend. Going through this crazy PhD roller coaster together, sharing the joy and pain of research has made it easier. I am so happy I got the chance to share it with you.

One of the greatest things that Amherst has given me is friendships that I know will last a lifetime. Rossy, John and Amy, thank you for standing by my side, offering your guidance and support, and cheering me on every step of the way. Rosario, the years I have shared with you in Amherst have been definitely the craziest, full of unforgettable moments from mid-day coffees to trips, to a crazy long quarantine and to lots and lots of UMass hockey at Mullins center. Thanks to Sara, Victor and Julia, hanging out with you has always been a wonderful breath of fresh air from the college life in Amherst and I am thankful for all the memories we created together.

Solveig, my ”american mom”, you have been a pillar of strength, unwavering belief in my abilities and unconditional support, thank you from the bottom of my heart. I feel incredibly blessed and fortunate to have you in my life.

To my whole family, thank you for all your unconditional love, support and encouragement from a far. To Pep, I can not help but tear up as I write this, losing you unexpectedly this past February has been one of the hardest things I have had to endure, you were a force of nature, you taught me that life is about working hard but also about enjoying it with your loved ones. You always told me to chase after my dreams, I am, and you are always with me. To my mom, words cannot express how
thankful I am for your endless belief and support, you are my greatest cheerleader, always there to help me up when I fall and celebrate my victories. Thank you for not letting me quit the 14536 times I said I wanted to. This accomplishment is as much yours as it is mine. Y por último, gracias a mi hermanito, a mi princesa, a mi sobrina favorita y mi niño Lobesno, mi iogrito, mi luz y ahora mi ángel. La mama te quiere inbinito, para siempre.

Gràcies.
REFINEMENT AND PERFORMANCE ANALYSIS OF THE STEPPED FREQUENCY MICROWAVE RADIOMETER IN EXTRA TROPICAL CYCLONE CONDITIONS

SEPTEMBER 2023

JEZABEL VILARDELL SÁNCHEZ
B.S., UNIVERSITAT POLITÈCNICA DE CATALUNYA (UPC)
M.Sc., UNIVERSITY OF MASSACHUSETTS AMHERST
Ph.D., UNIVERSITY OF MASSACHUSETTS AMHERST

Directed by: Professor Stephen J. Frasier

The Stepped Frequency Microwave Radiometer (SFMR) is a key instrument for estimation of ocean surface wind speed and rain rate in tropical and extra-tropical cyclones research. Through the observed brightness temperature \( T_B \) over a range of six C-band frequencies, the SFMR derives these key parameters used by hurricane specialists to issue watches and warnings. The information gathered with this instrument is also pivotal for post-storm studies and satellite calibrations. Currently, the SFMR requires an average time of 5-10 seconds of averaging to cycle through the six different frequency channels, so in regions with strong wind/rain gradients such as the eye wall of a hurricane, finer scale details can be overlooked. The University of Massachusetts Amherst Microwave Remote Sensing Laboratory (MIRSL) has developed a specialized version of the SFMR called UMass Simultaneous Frequency Microwave...
Radiometer (USFMR) that operates six frequency channels simultaneously, eliminating the averaging time. This project aims to assess the performance differences of these two sampling methods with data collected in the 2019 hurricane season, where the USFMR was installed alongside the operational SFMR aboard one of the NOAA WP-3D aircrafts.

The radiative transfer model (RTM) employed by the stepped frequency microwave radiometer (SFMR) and its application in airborne wintertime observations of high-latitude storms and extra tropical cyclones is considered. It is found that the current RTM, developed and tuned for use in tropical cyclones (TCs), does not adequately model the observed brightness temperatures typically encountered in these cold conditions. While the brightness temperatures observed at several frequencies across C-band are lower, they are more spread apart from each other than the TC RTM predicts. This study considers two hypotheses to explain the differences between the measurements and model. One hypothesis assumes the presence of a melting layer between the aircraft and the surface which imparts enhanced attenuation and emission, which would result in enhanced spreading of brightness temperatures. The properties of the melting layer scale with rain rate. The other hypothesis is a wind-dependent excess emissivity possibly due to a surface-based layer of mixed-phase droplets lofted from the surface. The latter hypothesis is most consistent with observations when the freezing level, as deduced from the flight-level temperature and an assumed lapse rate, is at or below the surface. It is found that the latter hypothesis appears to represent the observations better than the first, in large part because there is often little to no rain present in the observations. Finally, a scaling of the TC RTM’s wind excess emissivity is found to be required to obtain the best match with available dropsonde observations. An excess emissivity model for winter conditions is provided.

This project has been done in collaboration with NOAA/NESDIS/STAR and with funding support from the National Science Foundation through grant AGS-2016809.
TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>SECTION</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACKNOWLEDGMENTS</td>
<td>vi</td>
</tr>
<tr>
<td>ABSTRACT</td>
<td>ix</td>
</tr>
<tr>
<td>LIST OF TABLES</td>
<td>xiii</td>
</tr>
<tr>
<td>LIST OF FIGURES</td>
<td>xiv</td>
</tr>
<tr>
<td>CHAPTER</td>
<td></td>
</tr>
<tr>
<td>1. INTRODUCTION</td>
<td>1</td>
</tr>
<tr>
<td>2. THEORY AND BACKGROUND</td>
<td>5</td>
</tr>
<tr>
<td>2.1 Radiometry</td>
<td>5</td>
</tr>
<tr>
<td>2.2 Radiative Transfer Model</td>
<td>10</td>
</tr>
<tr>
<td>2.3 The Stepped Frequency Microwave Radiometer (SFMR)</td>
<td>13</td>
</tr>
<tr>
<td>2.4 Retrieval algorithm</td>
<td>14</td>
</tr>
<tr>
<td>2.4.1 Radiative Transfer Model for SFMR</td>
<td>16</td>
</tr>
<tr>
<td>2.4.1.1 Downward atmospheric contribution $T_{DOWN}$</td>
<td>18</td>
</tr>
<tr>
<td>2.4.1.2 Total sky contribution $T_{SKY}$</td>
<td>20</td>
</tr>
<tr>
<td>2.4.1.3 Upwelling contribution from the intervening atmosphere $T_{UP}$</td>
<td>20</td>
</tr>
<tr>
<td>2.4.1.4 Emission from the ocean surface $T_{OCEAN}$</td>
<td>21</td>
</tr>
<tr>
<td>3. UMASS SIMULTANEOUS FREQUENCY MICROWAVE RADIOMETER (USFMR)</td>
<td>24</td>
</tr>
<tr>
<td>3.1 Embedded system</td>
<td>26</td>
</tr>
<tr>
<td>3.1.1 Raspberry Pi</td>
<td>29</td>
</tr>
<tr>
<td>3.1.2 FPGA</td>
<td>32</td>
</tr>
<tr>
<td>3.1.3 Temperature control system</td>
<td>37</td>
</tr>
</tbody>
</table>
3.1.4 Integrator board .................................................. 38
3.1.5 Software .......................................................... 41

3.2 Calibration .......................................................... 43

4. HURRICANE LORENZO 2019 ........................................... 46
4.1 Brightness temperature comparison .................................. 49
4.2 Retrieved rain rate and wind speed .................................. 53
   4.2.1 Time domain .................................................. 53
   4.2.2 Frequency domain ............................................ 57

5. WINTER-TIME RETRIEVAL REFINEMENT FOR THE
   STEPPED FREQUENCY MICROWAVE RADIOMETER ........... 59
5.1 Excess emission from a melting layer ............................. 63
   5.1.1 Results with Melting Layer RTM ........................... 67
5.2 Excess emission from the surface ................................... 73
   5.2.1 $T_B$ behavior versus a reference wind speed .............. 74
   5.2.2 Results with SL RTM ........................................ 80
      5.2.2.1 Comparison in presence of Rain ....................... 86
5.3 Wind speed comparisons with GPS dropwindsondes ............. 88

6. CONCLUSIONS .......................................................... 98
6.1 Summary of USFMR system updates ............................... 99
6.2 SFMR & USFMR sampling methodology performance analysis ... 100
6.3 Refinement of the radiative transfer model for winter-time
      retrievals .......................................................... 102

7. APPENDIX I ........................................................... 106
8. APPENDIX II ........................................................... 109
9. APPENDIX III ........................................................... 113

BIBLIOGRAPHY .......................................................... 117
# LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1 SFMR specifications</td>
<td>13</td>
</tr>
<tr>
<td>3.1 USFMR specifications</td>
<td>26</td>
</tr>
<tr>
<td>3.2 Raspberry Pi 2 model B specifications</td>
<td>29</td>
</tr>
<tr>
<td>3.3 TinyFPGA BX specifications</td>
<td>33</td>
</tr>
<tr>
<td>3.4 Pinout table for the FPGA</td>
<td>33</td>
</tr>
<tr>
<td>3.5 Modes truth table</td>
<td>34</td>
</tr>
<tr>
<td>3.6 Sel1 and sel2 table</td>
<td>35</td>
</tr>
<tr>
<td>3.7 Specifications table of the block diagram circuit</td>
<td>39</td>
</tr>
<tr>
<td>3.8 Coefficients from the hot and cold calibration procedure from June 12th 2019</td>
<td>44</td>
</tr>
<tr>
<td>4.1 Calculated bias &amp; RMSE from Figure 4.8. (S) denotes OP SFMR data set smoothed (averaged)</td>
<td>54</td>
</tr>
<tr>
<td>4.2 Calculated bias &amp; RMSE from Figure 4.9 scatter plots. (S) denotes OP SFMR data set smoothed (averaged)</td>
<td>57</td>
</tr>
<tr>
<td>5.1 Calculated linear orthogonal regression (LOR), average bias, RMSE &amp; scaling factor from Figure 5.20</td>
<td>92</td>
</tr>
<tr>
<td>5.2 Calculated linear orthogonal regression (LOR), average bias &amp; RMSE from Figure 5.21</td>
<td>94</td>
</tr>
<tr>
<td>5.3 Calculated linear orthogonal regression (LOR), average bias &amp; RMSE from Figure 5.22</td>
<td>95</td>
</tr>
<tr>
<td>9.1 Calculated linear orthogonal regression (LOR), average bias &amp; RMSE from Figure 9.2</td>
<td>114</td>
</tr>
</tbody>
</table>
## LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td>Block diagram of a total power radiometer.</td>
<td>7</td>
</tr>
<tr>
<td>2.2</td>
<td>Block diagram of a Dicke radiometer.</td>
<td>8</td>
</tr>
<tr>
<td>2.3</td>
<td>Diagram of the main radiative contributors to the overall observed $T_B$ by an airborne nadir-looking radiometer.</td>
<td>11</td>
</tr>
<tr>
<td>2.4</td>
<td>SFMR modeled brightness temperature ($T_B$) obtained with the GMF reported in Sapp (2019) [14]. Right: $T_B$ for RR ($mm/hr$) from 0 mm/hr to 60 mm/hr assuming no wind. Left: $T_B$ for WS ($m/s$) from 0 m/s to 60 m/s assuming no rain. The colored lines correspond to different frequencies in C-Band from 4.7 GHz to 7.1 GHz, ordered from lowest to highest frequency.</td>
<td>12</td>
</tr>
<tr>
<td>2.5</td>
<td>Block diagram of the general structure of the retrieval algorithm of the SFMR.</td>
<td>14</td>
</tr>
<tr>
<td>2.6</td>
<td>Block diagram of the radiative contributions observed by the nadir-looking SFMR as described in Uhlhorn (2003) [2].</td>
<td>16</td>
</tr>
<tr>
<td>3.1</td>
<td>Block diagram of the USFMR.</td>
<td>24</td>
</tr>
<tr>
<td>3.2</td>
<td>Block diagram of the USFMR embedded system.</td>
<td>27</td>
</tr>
<tr>
<td>3.3</td>
<td>Picture of the new embedded system.</td>
<td>28</td>
</tr>
<tr>
<td>3.4</td>
<td>Raspberry Pi2 model B GPIO pins allocation. Red labels denote backup control signals generated directly by the Raspberry Pi.</td>
<td>30</td>
</tr>
<tr>
<td>3.5</td>
<td>Image of the TinyFPGA BX. (sourced from <a href="http://www.sparkfun.com">www.sparkfun.com</a>)</td>
<td>32</td>
</tr>
<tr>
<td>3.6</td>
<td>FPGA logic circuit.</td>
<td>35</td>
</tr>
<tr>
<td>3.7</td>
<td>Block diagram of integrator board circuit.</td>
<td>38</td>
</tr>
</tbody>
</table>
3.8 New integrator board prior to PCB assembly. ......................... 40

3.9 Block diagram of the USFMR software design. ......................... 41

3.10 Example of a raw data file generated by the USFMR measurements
(2019/06/12). ................................................................. 42

3.11 Brightness temperature (K) versus output voltage (V) from hot and
cold USFMR calibration procedure performed June 12<sup>th</sup> 2019. ...... 44

4.1 Best track positions for hurricane Lorenzo from September 23<sup>rd</sup> to
October 2<sup>nd</sup> (Figure 1 from NHC tropical cyclone report [35]).
The different colors on the track path denote the category of the
hurricane and the black arrow highlights its peak wind speed
location. ................................................................. 47

4.2 Flight path of N43RF aircraft on September 28<sup>th</sup> 2019 through
hurricane Lorenzo (top). The dash purple circle denotes an
approximation of the hurricane’s eye location for visual purposes.
X and Y axes are latitude and longitude in degrees, respectively.
USFMR lowest frequency channel brightness temperature ($T_B$)
measurement that matches the flight path depicted on the top
plot (bottom). The X axis is time in seconds relative to the flight
path and Y axis is $T_B$ in Kelvin. The different colors highlight
inbound and outbound passes of the eye-wall. ......................... 48

4.3 Brightness temperature measured with the lowest frequency channel
available in Kelvins as a function of time in seconds. Red and
cyan represent OP SFMR (4.74 GHz) and USFMR (4.63 GHz)
measured $T_B$, respectively. ............................................. 49

4.4 Brightness temperature difference between OP SFMR and USFMR
for the lowest frequency channels ($T_{BSFMR} - T_{BUSFMR}$) as a
function of time in seconds (top). Temperature inside the
USFMR box measured by a temperature sensor, expressed in
Celsius, as a function of time in seconds (bottom). ....................... 50

4.5 Brightness temperature measured with the lowest frequency channel
available in Kelvins as a function of time in seconds. Red
represents $T_B$ measured by OP SFMR (4.74 GHz) and green
depicts $T_B$ measured by USFMR (4.63 GHz) with temperature
correction. ................................................................. 51
4.6 Zoomed views of measured $T_B$ of inbound penetration of the hurricane eye wall for lowest frequency channel (OP USFMR offset by 5K for visual purposes). USFMR $T_B$ in black. OP SFMR in red and highlighted in blue to new measurements that get replicated while the channel remains idle. The green highlights in the USFMR data when does the OP SFMR update. X axis is time in seconds relative the full hurricane flight (Figure 4.5). Y axis represents $T_B$ in Kelvin. .......................... 52

4.7 Retrieved wind speed (top) and rain rate (bottom) for the whole hurricane flight. OP SFMR retrievals are shown in black and USFMR in red. X axis represents time in seconds and Y axes units are m/s (top) and mm/hr (bottom). .......................... 54

4.8 Scatter plot OP SFMR retrievals versus USFMR retrievals for wind speed (left) and rain rate (right). The green dotes show OP SFMR retrievals obtained with $T_B$'s averaged with a 10 sample window and black without averaging. Units are m/s (left) and mm/hr (right). .......................... 55

4.9 Zoomed view of retrieved wind speed in m/s (blue-OP SFMR, green-USFMR) and rain rate in mm/hr (red-OP SFMR, black-USFMR) over time in seconds of two different eye-wall passes (1st & 3rd row) for OP SFMR averaged (right column) and not averaged (left column). The 2nd & 4th row show corresponding scatter plots for rain rate (left) and wind speed (right) comparing averaging effect over the OP SFMR versus USFMR retrievals (green is averaging, black is without). .......................... 56

4.10 Variance spectrum in logarithmic scale of SFMR retrieved wind speed (left) and rain rate (right) of the whole hurricane flight. Black denotes retrievals obtained with the OP SFMR without averaging $T_B$. Green shows the OP SFMR retrievals with $T_B$ averaged over 10 samples and red is the USFMR retrieved data. .......................... 58

5.1 Retrieved rain rate in mm/hr (black) and wind speed in m/s (red) for 1h interval from flight on February 28th, 2021 out of Anchorage (AK), USA implementing NOAA/NESDIS RTM algorithm described in Sapp (2019) [14]. .......................... 60
5.2 SFMR modeled brightness temperature ($T_B$) obtained with the geophysical model function (GMF) reported in Sapp (2019) [14] with typical tropical environmental conditions (solid lines) and winter-time extra-tropical conditions (dashed lines). Left: $T_B(WS)$ assuming no rain. Right: $T_B(RR)$ assuming no wind. The colored lines correspond to different frequencies in C-Band from 4.7 GHz to 7.1 GHz, with the higher frequencies corresponding to higher $T_B$. .................................................. 61

5.3 Diagram of the proposed melting layer RTM radiative contributions to the total $T_B$ measured by the SFMR. ................................. 63

5.4 Example of modeled C-Band specific attenuation for different effective medium approximations. Figure 9 from von Lerber, A. (2015) [39]. ................................................................. 65

5.5 SFMR modeled brightness temperature ($T_B$) obtained with the melting layer (ML) radiative transfer model (RTM) with winter-time extra-tropical conditions. The colored lines correspond to different frequencies in C-Band from 4.7 GHz to 7.1 GHz, with the higher frequencies corresponding to higher $T_B$. ....... 66

5.6 Estimated $H_r$ (red) and aircraft altitude (black) in meters for winter flight February 5$^{th}$ 2012 as a function of time in seconds since 16:10 UTC (top). Corresponding SFMR retrieved rain rate (mm/hr) as a function time (in seconds) implementing Sapp 2019 RTM (black) or ML RTM (red) (bottom). The dashed blue lines highlight in time (vertical) and in $H_r$ height (horizontal) where the retrieved rain rate values become highly erratic. .............................. 68

5.7 IWRAP vertical reflectivity profiles in dBZ for four consecutive time intervals of 10 minutes starting at 16:10 UTC. Data from February 5$^{th}$ 2012. ................................................................. 69

5.8 Data from February 3$^{th}$ 2012. Top: IWRAP vertical reflectivity profile in dBZ as a function of distance in km for a time interval of 10 minutes starting at 18:00 UTC. Middle and bottom plots: Retrieved rain rate (mm/hr) and wind speed (m/s), respectively, as a function of time in seconds for Sapp 2019 RTM (black) and ML RTM (red). ................................................................. 70
5.9 Left: mean measured $T_B$ in Kelvin (solid lines) and modeled $T_B$ (dashed lines) for five different frequency channels as a function of $U_{ref}$ from January 28th 2014. Higher frequency channels are offset as indicated for clarity. Right: mean $T_B$ difference in Kelvin (measured minus modeled) as a function of $U_{ref}$. Error bars denote ±1 standard deviation of the $T_B$ difference. ...................... 74

5.10 Diagram of the proposed surface layer RTM radiative contributions to the total $T_B$ measured by the SFMR. ......................... 76

5.11 Averaged emissivity of SL as a function of wind speed ($U_{ref}$) in m/s. Dashed lines show the linear fit for each of the frequency channels. ................................................................. 78

5.12 Total count of averaged samples in the emissivity of the surface layer as a function of wind speed in m/s. The vertical blue line denotes the threshold under which the sample count is insufficient. .......... 79

5.13 SFMR modeled brightness temperature as a function of wind speed ($T_B(WS)$) obtained with Sapp 2019(left) and surface layer(SL)(right) radiative transfer model (RTM) with winter-time extra-tropical conditions and $H_r = 0$ m. The colored lines correspond to different frequencies in C-Band from 4.7 GHz to 7.1 GHz, with the higher frequencies corresponding to higher $T_B$. ............ 80

5.14 Data from February 2nd 2013. Top: Aircraft altitude (black) and $H_r$ (red) in meters. Middle: Retrieved rain rate in mm/hr with Sapp 2019 (black), SL (red) and ML (cyan) RTMs. Bottom: Retrieved wind speed in m/s with Sapp 2019 (black), SL (red) and ML (cyan) RTMs. All plots as a function of time in seconds since 00:30 UTC. Black dashed vertical lines denote time interval where $H_r > 0m$. ................................................................. 82

5.15 Scatter plot comparing retrieved wind speed with Sapp 2019 RTM against ML RTM (dark blue $H_r > 0m$, cyan $H_r < 0m$) and SL RTM (green $H_r > 0m$, red $H_r < 0m$) in m/s. ..................... 83

5.16 Top: Retrieved rain rate with Sapp 2019 RTM (black) and SL RTM (red) as a function of time in seconds. Bottom left: Retrieved wind speed with Sapp 2019 RTM (black), SL RTM (red) and ML RTM(cyan) in m/s. Bottom right: Scatter plot comparing retrieved wind speed in m/s for Sapp 2019 RTM against SL RTM (black) and ML RTM (cyan). All the retrievals have a floor for $H_r$ set at 200m. ................................................................. 84
5.17 Data from February 3\textsuperscript{th} 2012. Top: IWRAP vertical reflectivity profile in dBZ as a function of distance in km for a time interval of 10 minutes starting at 18:00 UTC. Middle and bottom plots: Retrieved rain rate (mm/hr) and wind speed (m/s), respectively, as a function of time in seconds for Sapp 2019 RTM (black), SL RTM (red) and ML RTM (cyan). 

5.18 Scatter plot comparing 10m neutral wind speed $U_{10N}$ ($speed_{interp}$) obtained with GPS dropsondes against retrieved SFMR wind speed with the lowest frequency channel assuming zero rain rate ($U_{ref}$) in m/s. SFMR data retrieved with Sapp 2019 RTM. Green line shows the linear orthogonal regression of the data.

5.19 Scatter plot comparing 10m wind speed ($speed_{interp}$) obtained with GPS dropsondes against retrieved SFMR wind speed with the lowest frequency channel assuming zero rain rate ($U_{ref}$) in m/s employing Sapp 2019 RTM with a scaling factor of 1.38 applied to $\varepsilon_{ws}$. The dashed black lines show the corresponding linear orthogonal regression.

5.20 Scatter plot comparing $U_{10N}$ ($speed_{interp}$) from GPS dropsondes against retrieved SFMR wind speed with different reference frequency channel assuming zero rain rate ($U_{ref}$) in m/s. Each row uses a different frequency channel: a-b) 5.57 GHz, c-d) 6.02 GHz, e-f) 6.69 GHz and g-h) 7.09 GHz. SFMR data retrieved with Sapp 2019 RTM unmodified(left) and with scaling factors applied to the surface excess emissivity due to wind speed ($\varepsilon_{ws}$).

5.21 Scatter plot comparing 10m wind speed ($speed_{interp}$) obtained with GPS dropsondes against SFMR wind speed retrieved with variations of Sapp 2019 RTM: a) original Sapp 2019 RTM, b) Positive rain column depth floor set at 200m ($H_r$), c) $\varepsilon_{ws}$ scaled by 1.38 and $H_r > 200m$ and d) $\varepsilon_{ws}$ scaled by 1.31 and $H_r > 200m$. Dashed lines show the linear orthogonal regression. Units are m/s.

5.22 Scatter plot comparing 10m neutral wind speed ($speed_{interp}$) obtained with GPS dropsondes against SFMR wind speed retrieved with SL RTM (black) and ML RTM (cyan) unmodified(left) and with scaling factors applied to the surface excess emissivity due to wind speed ($\varepsilon_{ws}$), 1.31 and 1.138, respectively. Units are m/s.
5.23 Data from February 3rd 2012. Retrieved rain rate (RR) in mm/hr as a function of time in seconds for Sapp 2019 RTM (black), ML RTM (cyan) and SL RTM (red). Solid lines correspond to RR retrieved with a scaling factor applied to $\varepsilon_{ws}$ for Sapp 2019, ML and SL RTMs. Dashed lines show RR without the scaling factor in the RTMs. ................................................................. 96

7.1 Logic diagram for Horizontal port selection in the tinyFPGA (truth Table (3.5)) ................................................................. 106

7.2 Logic diagram for Vertical port selection in the tinyFPGA (truth table (3.5)) ................................................................. 107

7.3 Logic diagram for Reference port selection in the tinyFPGA (truth table (3.5)) ................................................................. 107

7.4 Logic diagram for Calibration (noise source) port selection in the tinyFPGA (truth table (3.5)) ................................................................. 108

8.1 Integrator board layout designed with Altium: PCB design and Software tools. ................................................................. 109

9.1 Scatter plot comparing 10m neutral wind speed $U_{10N}$ ($speed_{interp}$) obtained with GPS dropsondes against retrieved SFMR wind speed with the lowest frequency channel assuming zero rain rate ($U_{ref}$) in m/s. Black and cyan dots show SFMR data retrieved with Sapp 2019 RTM and Klotz 2014 RTM, respectively. Dashed lines show the linear orthogonal regression of the data. ............ 113

9.2 Scatter plot comparing 10m wind speed ($speed_{interp}$) obtained with GPS dropsondes against SFMR wind speed retrieved with variations of Klotz 2014 RTM: a) original Klotz RTM, b) Positive rain column depth floor set at 200m ($H_r$), c) $\varepsilon_0$ scaled by 1.0195 and $H_r > 200m$ and d) $\varepsilon_0$ scaled by 1.0095 and $H_r > 200m$. Dashed lines show the linear orthogonal regression. Units are m/s. ................................................................. 115

9.3 Data from February 3rd 2012. Retrieved rain rate (RR) in mm/hr as a function of time in seconds for Klotz 2014 RTM. Solid lines correspond to RR retrieved with a scaling factor applied to $\varepsilon_0$. Dashed lines show RR without the scaling factor in the RTM. ........ 116
CHAPTER 1
INTRODUCTION

Microwave radiometers are highly sensitive receivers that passively measure electromagnetic emission by natural media. The goal of a radiometer is to measure power. In microwave applications, it is expressed in terms of an equivalent temperature that incorporates all the radiative contributions observed by the antenna. Microwave radiometers have been widely used for many decades in remote sensing fields such as astronomy or environmental applications, including planetary mapping, atmospheric profiling, soil moisture measurements, etc [1]. This project focuses on the application of microwave radiometers, in particular the Stepped Frequency Microwave Radiometer (SFMR), for ocean surface wind speed and columnar rain rate estimation in oceanic storms.

The SFMR is a nadir-looking, aircraft-based, C-band radiometer that steps through 6 different frequency channels to measure upwelling radiative emission generated by the ocean surface, driven by the wind and the intervening atmosphere, in the form of what is called brightness temperature ($T_B$) [2]. It is broadly used in hurricane reconnaissance as well as in research missions of tropical cyclones (TC) and extratropical cyclones (ETC) aboard the National Oceanic and Atmospheric Administration (NOAA) WP-3D and the U.S. Air Force Reserve Command (AFRC) WC-130J aircrafts.

The original concept for the SFMR was proposed by C. T. Swift of NASA’s Langley Research Center and built in 1978 [3]. It was flown for the first time in 1980, through Hurricane Allen, aboard a NOAA C-130 aircraft. The measure-
ments collected were used to develop an algorithm for retrieving ocean surface winds and column-averaged rain rate below the aircraft [4]. Later on, SFMR instrument and algorithm development were subsequently undertaken at the University of Massachusetts Amherst where Swift had moved to co-direct the Microwave Remote Sensing Laboratory (MIRSL). SFMR developments continued through the 1980s and early 1990s [5, 6, 7, 8, 9].

In the mid 1990s a modified SFMR was developed for NOAA’s Hurricane Research Division (HRD) by Quadrant Engineering (now ProSensing) of Amherst, MA. By this time, hurricane research missions began obtaining wind and thermodynamic profiles via dropwindsondes, which are GPS dropsondes deployed from the aircraft to measure temperature, humidity, pressure, and specially winds between flight level and the surface [10]. The first exhaustive intercomparison of co-located near-surface winds by this SFMR and dropwindsondes in tropical cyclones was published by Uhlhorn (2003) [2], proving valuable estimation of ocean surface wind speed with SFMR measurements.

Subsequent to the disastrous 2005 hurricane season, with landfalling storms such as Katrina, which caused over 1800 fatalities and over $125 billion in damage, and Rita, which caused 120 fatalities and over $18.5 billion in damage, SFMR instruments were procured and installed on the NOAA research aircrafts (WP-3D and Gulfstream IV) and the Air Force 53rd Weather Squadron’s WC-130J operational reconnaissance aircraft. Over time, the availability of more observations made possible the refinement of the microwave emissivity and absorption models implemented to retrieve the wind and rain rate from the observed $T_B$ [11, 12, 13, 14].

The current state-of-the-art model proves very effective in tropical cyclone environments providing accurate measurements of ocean surface wind speed and rain rate. However, when measurements are performed over extra-tropical cyclones, specifically high-latitude winter storms, the retrieval has been reported to diverge from other ground truth sources, retrieving erroneously high rain rates. ETCs are low-pressure
weather systems capable of producing wind speeds that can reach hurricane force and could result in storm surges, such as high astronomical tides, posing a threat to coastlines. They usually form anywhere within the extra-tropical region of the Earth, most often between 30^º and 60^º latitude from the equator. The SFMR retrieval fails to perform well in ETCs largely because the algorithm was developed with a specific focus on the tropical environment where hurricanes form. All the models implemented in the algorithm have been molded to describe the TC climate, making assumptions about the surrounding atmosphere that are not applicable to the ETCs region. Among the issues that impact the SFMR’s observations are geophysical parameters such as sea surface temperature (SST) or ambient temperature ($T_a$), which are significantly lower, and the altitude of wet precipitation, if present, relative to flight level and surface hydrodynamics. Adjustment of the current model is required to properly retrieve data outside the TC environment. The main goal is to generate a model that can properly adapt to whatever different environments the SFMR is being deployed.

This project also addresses the matter of the effective averaging time of radiometric measurements, and how this could conceivably affect the observation of fine-scaled features in the precipitation environment, regions with strong wind gradients, or gust features on the sea surface. The SFMR measures over the six available frequency channels sequentially, the time between independent complete observations is reported to be 5-10 seconds [2], which corresponds to an averaging distance of up to 1.5km. This time interval in-between observations can corrupt or conceal fine-scale features previously mentioned.

In the late 1990s, MIRSL developed a simultaneously sampling SFMR instrument, which allowed parallel measurements over frequency enabling more rapid updates [15]. The UMass SFMR (USFMR), in the early 2000s, flew in tandem with airborne scatterometers as their ground-truth source [16, 17], however, its development was discon-
continued following the permanent installation of the commercial SFMR, also referred to as operational SFMR, on the NOAA aircrafts.

In 2018 an opportunity to install the USFMR in one of the NOAA WP-3D aircrafts for the 2019 hurricane season arose given a space vacancy. The purpose of the deployment of the USFMR was to obtain data to assess the differences in simultaneous vs. sequential sampling by comparing data collected by the USFMR and the commercial SFMR already installed in the P-3 aircraft, focusing on the fidelity of the observations of fine-scale features in the wind and rain fields. Updates to both hardware and software of the USFMR instrument were required, all reported in this project.
2.1 Radiometry

A radiometer is a sensitive receiver designed to measure noise power. It obtains information about its target from the microwave portion of the blackbody radiation spectrum [1]. In thermodynamic equilibrium, a blackbody at a physical temperature $T$ radiates energy according to Planck’s radiation law. A blackbody is an ideal material that absorbs all incident radiation at all frequencies and reflects none. At thermal equilibrium a blackbody not only is a perfect absorber but also a perfect emitter if its physical temperature remains unchanged [18].

In the microwave region, this blackbody radiation is measured through radiated power with the following equation:

$$P = k \cdot T \cdot B$$

(2.1)

where $k$ is the Boltzmann’s constant and $B$ is the system’s bandwidth.

However, this equation is only applicable to blackbodies. For non-ideal materials, which reflect some of the incident radiation, the radiated power of the material relative to that radiated by a blackbody at the same physical temperature $T$ given by the emissivity:

$$\varepsilon = \frac{P}{kTB}$$

(2.2)

where $P$ is the power radiated by the non-ideal body and $kTB$ is the emitted power by a blackbody. This is a unitless variable that ranges from 0 to 1, $\varepsilon = 1$ being the emission of a blackbody.
This measured power $P$ can also be expressed in terms of equivalent temperature, in radiometry, it is brightness temperature $T_B$:

$$T_B = \varepsilon \cdot T.$$  \hfill (2.3)

From this point on, the variable $P$ is expressed in terms of $T_B$. The unit of $T_B$ is Kelvin.

A radiometer measures a portion of the power received by the antenna over a given bandwidth given a center frequency, according to [19]:

$$P = k \cdot G \cdot B \cdot T_A.$$  \hfill (2.4)

where $T_A$ is the antenna temperature and $G$ is the gain of the radiometer receiver. The antenna temperature is the observed brightness temperature weighted by the antenna’s radiation pattern.

However, this equation is only for an idealized radiometer, in real life the instrument will also generate noise that will be added to the input signal:

$$P = k \cdot G \cdot B \cdot (T_A + T_N)$$  \hfill (2.5)

where $T_N$ is the noise temperature of the system.

The radiometer measurement process is characterized by accuracy and precision. Given (2.5), ideally, $k$, $B$, $G$ and $T_N$ should be known constants, however, in real life $G$ and $T_N$ may not be stable enough to satisfy reasonable requirements for accuracy. Steps towards accuracy include calibration of the instrument.

Another important concept is the radiometric sensitivity of the radiometer, $\Delta T$, defined as the smallest change in $T_A$ perceivable by the instrument.
\[
\Delta T = \frac{T_A + T_N}{\sqrt{B \cdot \tau}} \tag{2.6}
\]

where \( \tau \) is the integration time. This formula corresponds to the \( \Delta T \) of a total power radiometer (TPR).

Figure 2.1. Block diagram of a total power radiometer.

Figure 2.1 shows a block diagram of a total power radiometer which is the simplest type of radiometer. The gain of the instrument is represented by an amplifier with gain \( G \), then a band pass filter with a center frequency and bandwidth \( B \) of 100 MHz. After that, a detector measures the instantaneous power. To detect the received power, a square-law detector is used, which gives an output voltage proportional to the input power, and hence the noise temperature of the target. Finally, an integrator is used to smooth the signal from the detector to reduce fluctuations in the output. The smoothing of the signal is directly proportional to the integration time, the longer the \( \tau \) the smoother the output signal. The output can be expressed as:

\[
V_{out} = c \cdot (T_A + T_N) \cdot G \tag{2.7}
\]

where \( c \) is a constant, which includes \( k \) and \( B \).

As can be seen, the output voltage is totally dependent on the noise temperature and the gain of the system. As previously mentioned, these two variables may not be stable enough to fulfill the accuracy requirements. Frequent calibration is one of the approaches when using a total power radiometer, but another strategy to mitigate this issue is the Dicke radiometer [19], which is the chosen radiometer design for both the SFMR and the USFMR.
A Dicke radiometer does not measure the antenna temperature directly. Instead, it measures the difference between the antenna temperature and some known reference temperature \( T_R \). Using this method of indirect measurement of \( T_A \) alleviates the instabilities caused by \( T_N \) and \( G \).

\[ V_1 = c \cdot (T_A + T_N) \cdot G, \]
\[ V_2 = c \cdot (T_R + T_N) \cdot G \]  

(2.8)

Assuming that the frequency of the switch is rapid enough, \( T_A, T_N \) and \( G \) are considered constant over the period, and this period is much shorter than the integration time. The output of the Dicke radiometer can be found to be:

\[ V_{out} = V_1 - V_2 = c \cdot (T_A - T_R) \cdot G \]  

(2.9)

Using this method, \( T_N \) is eliminated and \( G \), while still present, has less weight. Even though the Dicke radiometer lessens the impact of instabilities, the radiometric

**Figure 2.2.** Block diagram of a Dicke radiometer.
sensitivity is reduced. Now the radiometer only spends half of the time looking at the antenna signal hence the sensitivity is poorer. The output of the Dicke radiometer can be understood as the difference between two total power radiometers, TPR1 for the antenna and TPR2 for the known reference, each with an integration time of $\tau/2$ and sensitivities $\Delta T_1$ and $\Delta T_2$ respectively (2.10).

\[
\begin{align*}
\Delta T_1 &= \frac{T_A + T_N}{\sqrt{B \cdot \tau/2}}, \\
\Delta T_2 &= \frac{T_R + T_N}{\sqrt{B \cdot \tau/2}}.
\end{align*}
\]

(2.10)

The sensitivity of the radiometer can be determined by:

\[
\Delta T = 2 \cdot \frac{T_A + T_N}{\sqrt{B \cdot \tau}}.
\]

(2.11)

In the above, $T_A$ can also be replaced by $T_R$ giving us a more conservative version of the sensitivity given that $T_R > T_A$. Because of the switching, the sensitivity of a Dicke radiometer is reduced by a factor of 2 compared to the total power radiometer.
2.2 Radiative Transfer Model

The SFMR measures upwelling C-band radiation emission generated by the sea surface and the intervening atmosphere [2]. The primary contributors to variation of ocean surface emissivity are surface roughness and presence of foam driven by the ocean surface wind speed [20]. The three main mechanisms that influence the roughness scale are:

1. Large gravity waves whose wavelengths are long compared to the radiation wavelength.
2. Small capillary waves that ride on top of the large-scale waves.
3. Sea foam generated at wind speeds about 7 m/s.

The apparent $T_B$ measured by the SFMR also accounts for other radiative contributions such as the surrounding atmosphere. The emissivities of the ocean, the rain, and the atmosphere depend on their thermodynamic states and physical compositions, characterized by variables such as sea surface temperature ($SST$), salinity, air temperature ($T_a$), pressure and moisture.

The radiative transfer model (RTM) is the set of equations that describe the flow of radiant energy to be measured by the radiometer [21], so that all the contributions of the ocean and the atmosphere to the overall measured $T_B$ are included.

Figure 2.3 shows a diagram illustrating all of the contributors to the overall observed $T_B$ considered in the RTM. The total observed radiative contributions by the airborne nadir-looking radiometer include the following emissions:

- The downward emission of the atmosphere (DEA).
- The reflected DEA by the ocean surface.
- The self-emission of the ocean surface.
• The self-emission of the intervening atmosphere, which can include the emission of the rain, if present.

**Figure 2.3.** Diagram of the main radiative contributors to the overall observed $T_B$ by an airborne nadir-looking radiometer.

Moreover, the intervening atmosphere has an attenuation effect over the emission of the ocean surface and the DEA also included in the RTM.

Figure 2.4 shows an example of modeled $T_B$ observed by the SFMR obtained with the current RTM for typical tropical environment. In this figure, two different plots are shown. The plot to the left shows modeled $T_B$ for wind speed (WS) from 0 to 60 m/s assuming no rain. The wind speed dependence of $T_B$ is nearly independent of frequency as all the channels vary at the same rate. For wind speeds below 15 m/s the $T_B$ is weakly dependent on wind speed as the excess emissivity of the ocean is due to surface roughening only. For higher wind speeds, the generation of foam on the surface, due to wave breakage, leads to a stronger $T_B$ dependence on wind speed.

The one on the right shows modeled $T_B$ for rain rate (RR) from 0 to 60 mm/hr assuming no wind. In this plot, it can be seen the strong dependence on frequency for
$T_B$ when rain is present. As RR increases the different frequency channels show more spread for higher frequencies given that at C-Band, rain is a measurable absorber of radiation, for higher frequencies RR absorption is stronger because raindrop size is similar to the frequency wavelength which results in more scattering of the signal leading to greater attenuation and emission from the raindrops [12].

**Figure 2.4.** SFMR modeled brightness temperature ($T_B$) obtained with the GMF reported in *Sapp* (2019) [14]. Right: $T_B$ for RR (mm/hr) from 0 mm/hr to 60 mm/hr assuming no wind. Left: $T_B$ for WS (m/s) from 0 m/s to 60 m/s assuming no rain. The colored lines correspond to different frequencies in C-Band from 4.7 GHz to 7.1 GHz, ordered from lowest to highest frequency.
2.3 The Stepped Frequency Microwave Radiometer (SFMR)

This section briefly describes the commercial/operational SFMR used in this project. As described in [22], the Stepped Frequency Microwave Radiometer (SFMR) is the primary instrument used by the National Hurricane Center to determine hurricane intensity. SFMR is an airborne radiometer designed to measure surface brightness temperature in six frequency bands spanning 4.6 to 7.2 GHz. Calibrated values of brightness temperature generated by SFMR are reported in real-time to a wind speed retrieval algorithm, developed in cooperation with NOAA’s Hurricane Research Division. This algorithm generates a real-time measure of surface level wind speed and rain rate in hurricanes and tropical storms. Each of the Air Force Reserves’ C-130 Hurricane Hunter aircraft is equipped with an SFMR, as are NOAA’s P-3 and Gulfstream 2 hurricane research aircraft. Table 2.1 shows the SFMR specifications as described in [22].

Table 2.1. SFMR specifications

<table>
<thead>
<tr>
<th>Radiometer type</th>
<th>hach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Center frequencies</td>
<td>4.74, 5.31, 5.57, 6.02, 6.69 and 7.09 GHz</td>
</tr>
<tr>
<td>Receiver BW</td>
<td>100 MHz</td>
</tr>
<tr>
<td>Polarization</td>
<td>linear</td>
</tr>
<tr>
<td>Antenna</td>
<td>corrugated horn</td>
</tr>
<tr>
<td>Beamwidth</td>
<td>20°-28°</td>
</tr>
<tr>
<td>System noise temperature</td>
<td>490K</td>
</tr>
<tr>
<td>Radiometric precision</td>
<td>0.4K</td>
</tr>
</tbody>
</table>
2.4 Retrieval algorithm

This section provides an overview of the retrieval algorithm implemented to obtain wind speed and rain rate from observed brightness temperatures. Over the years, this retrieval has undergone several updates and improvements as documented in previous studies [2, 7, 11, 13, 14]. It is important to note that these modifications have solely focused on the accuracy of the instrument in tropical cyclones.

The operational flow of the retrieval algorithm is summarized in the block diagram depicted in Figure 2.5. The algorithm operates on the premise that given an array of measured brightness temperatures \( T_B \), with their corresponding frequencies at which they were measured, along with relevant parameters of the surrounding environment such as flight-level air temperature \( T_a \), sea surface temperature (SST) and so on, it estimates the corresponding wind speed and rain rate employing the Gauss-Newton procedure.

The Gauss-Newton procedure is an optimization iterative algorithm used to solve nonlinear least squares problems. It involves minimizing the sum of the squares of the difference between the measured values, which are the brightness temperatures \( T_B \), and the values predicted by a prediction model, which in this case is the radiative transfer model (RTM).

**Figure 2.5.** Block diagram of the general structure of the retrieval algorithm of the SFMR.
The procedure starts with an initial guess for wind speed and rain rate, usually provided in the input parameters. The conventional default values are 10 m/s and 0 mm/hr, respectively. These two values are updated in each iteration of the procedure until convergence is achieved. In this context, it is defined as the point at which the root-mean-square of the solution should change by less than 1%.

Currently, the retrieval algorithm allows for a maximum of 20 iterations and the wind speed and rain rate guesses are incremented by one in each iteration.

The retrieval algorithm requires the following input parameters:

- Brightness temperatures ($T_B$) in Kelvin. Array of size determined by the number of frequency channels.
- Center frequencies of the channels measuring the $T_B$s in GHz.
- Sea surface temperature (SST) in Celsius.
- Salinity in psu (practical salinity unit).
- Altitude of the aircraft at the moment of the $T_B$ measurement in meters.
- Flight level air temperature ($T_a$) in Celsius.
- Initial guess for wind speed (m/s) and rain rate (mm/hr) such as (10,0).
- Empty array of same size as $T_B$ to store the $T_B$ error (measured $T_B$ minus modeled $T_B$)

In addition to the listed parameters, there exist several optional input parameters which can be utilized to customize the algorithm’s functionality. These include the ability to select a specific radiative transfer model (RTM), the default being the Sapp 2019 RTM [14], as well as the option to omit specific channels or manually set the rain column depth ($H_r$), among other potential features.
The retrieval algorithm creates an array of five elements, those being: 1.) the estimated wind speed in m/s, 2.) the estimated rain rate in mm/hr, 3.) the root-mean-square error of the difference between measured and modeled $T_B$ (Tberr), 4.) the number of iterations executed by the algorithm to derive a solution, and 5.) a status variable, that provides valuable insights in the event that the retrieval fails to produce a valid outcome. This status variable can help pinpoint the specific location within the code where the error occurred, facilitating effective debugging and troubleshooting.

### 2.4.1 Radiative Transfer Model for SFMR

In this section a detailed description of the radiative transfer model currently used by NOAA/NESDIS and in this study is provided (Sapp 2019 [14]).

![Block diagram of the radiative contributions observed by the nadir-looking SFMR as described in Uhlhorn (2003) [2].](image)

**Figure 2.6.** Block diagram of the radiative contributions observed by the nadir-looking SFMR as described in *Uhlhorn* (2003) [2].
This geophysical model has been thoroughly studied and validated with independent measurements from global positioning system (GPS) dropwindsondes and other instruments aboard the aircraft.

Figure 2.6 shows a diagram of all radiative contributions to the total $T_B$ observed by the SFMR [18, 2]. These include:

- The downwelling cosmic microwave background radiation attenuated by the atmosphere and reflected by the ocean surface ($T_{\text{cos}} = 2.73K$);

- The downward emission by the atmosphere reflected by the ocean surface ($T_{\text{DOWN}}$);

- The upward emission from the surface attenuated by the intervening atmosphere ($T_{\text{OCEAN}}$);

- The upwelling emission from the intervening atmosphere ($T_{\text{UP}}$).

At C-band frequencies, the main contributors to the absorption, emission and transmission of the atmosphere are primarily governed by the absorption of oxygen molecules, water vapor molecules and absorption and scattering of liquid water particles [2]. In addition, at C-band frequencies, the intervening atmosphere is relatively transparent due to the frequency separation from the 22 GHz water vapor and the 60 GHz oxygen absorption bands [23].

The individual contributions to the observed brightness temperature depicted in Figure 2.6 and their combination are summarized in the following equations, as described in Sapp(2019) [14]:
\[ T_{DOWN} = (1 - \tau_r,\infty)(T_r,\infty) + \tau_r,\infty \cdot (1 - \tau_a,\infty)(T_a,\infty) \] (2.12)

\[ T_{SKY} = [T_{DOWN} + \tau_r,\infty \cdot \tau_a,\infty \cdot T_{cos}] \cdot (1 + \Omega) - (\Omega \cdot T_{cos}) \] (2.13)

\[ T_{UP} = (1 - \tau_{r,A/C} \cdot \tau_{a,A/C})(T_{a,A/C}) \] (2.14)

\[ T_{OCEAN} = \varepsilon \cdot SST \] (2.15)

\[ T_B = \tau_{r,A/C} \cdot \tau_{a,A/C} \cdot (T_{OCEAN} + (1 - \varepsilon)T_{SKY}) + T_{UP}. \] (2.16)

**2.4.1.1 Downward atmospheric contribution** \(T_{DOWN}\)

Equation (2.12) provides a definition of the downwelling atmospheric contributions, accounting for both the gaseous components throughout the entire atmospheric column and the hydrometeor contributions for the total rain column [2]. The variable \(T\) represents the physical temperature in Kelvins, the subscripts \((r, \infty)\) and \((a, \infty)\) refer to rain and atmospheric contributions by the total atmospheric column, set at 30km and the total rain column (i.e., the freezing level) \(H_r\), respectively. The angle brackets imply a mass-weighted layer average, and \(\tau\) is transmissivity.

In the initial formulation described by Uhlhorn (2003) [2], the set of RTM equations assumed a fixed total rain column of 4 km depth, which is typical of tropical conditions. However, subsequent analyses comparing the rain rate estimates derived from the SFMR with those obtained from radar-based measurements revealed a systematic tendency. Specifically, the SFMR algorithm tended to overestimate weak rain rates while underestimating strong rain rates[12]. It was concluded that the bias could be attributed to a variation of the rain column depth which directly affects the calculation of the absorption coefficient of the rain. The work by Klotz (2014) [13] introduced a modification for determining \(H_r\), estimating it from the flight-level air temperature \((T_a\text{ in Kelvin})\) and altitude of the aircraft:

\[ H_r = h + \gamma^{-1} \cdot T_a \] (2.17)
where \( h \) is the altitude of the aircraft in meters and \( \gamma \) corresponds to the mean atmospheric lapse rate, which is determined as \( \gamma = 5.22 \times 10^{-3} \text{K/m} \). This value is derived from an extensive collection of dropsonde temperature profiles obtained through the years in hurricanes [24]. The Sapp 2019 RTM also uses this approach to estimate \( H_r \).

The transmissivity of the rain column \( \tau_r \) solely depends on hydrometeor content, which is proportional to rain rate and electromagnetic frequency. Given the small ratio of raindrop size to the SFMR electromagnetic wavelength, scattering effects can be considered negligible, even at high rain rates [2]. The correlation between the transmissivity of the rain column, \( \tau_r \), and the rainfall absorption coefficient, denoted as \( \kappa_r \), is expressed as follows:

\[
\tau_{r,\infty} = e^{-\kappa_r H_r}.
\]  

(2.18)

The rainfall absorption coefficient is modeled by an empirical \( \kappa - R \) relationship with four parameters, widely studied and developed through the years [25, 2, 11, 12, 14]:

\[
\kappa_r(f, R) = g \cdot f^{n(R)} \cdot R^b.
\]  

(2.19)

\[
n(R) = c \cdot R^d
\]  

(2.20)

where \( f \) is frequency, \( R \) is rain rate and \( g, b, c, d \) are the empirical parameters.

The transmissivity of the atmosphere (\( \tau_{a,\infty} \) is a quadratic formula as a function of frequency, given by:

\[
\tau_{a,\infty} = (1 - p_0) + p_1 \cdot f + p_2 \cdot f^2
\]  

(2.21)

The coefficients \( p_0, p_1 \) and \( p_2 \) are derived empirically from the water vapor and oxygen absorption model, which uses the total integrated gaseous transmissivities [14]. Prior
RTM models characterized $\tau_{a,\infty}$ as a linear function, and the coefficients for the atmospheric absorption model were determined in Wentz (2016) [26]. However, in the most recent revision of the RTM conducted by Sapp (2019) [14], it was determined that the prior model exhibited an inaccurate frequency dependence and slightly lower values.

2.4.1.2 Total sky contribution $T_{SKY}$

The total downwelling sky radiation $T_{SKY}$, as expressed in equation (2.13), includes the total downward radiation of the atmosphere ($T_{DOWN}$), the downwelling cosmic microwave background radiation attenuated by both the atmospheric and rain column and the atmospheric path length correction for the downwelling sky radiation scattered off the surface. $\Omega$ characterizes the strength of the atmospheric path correction determined in the Remote Sensing Systems (RSS) RTM [27].

2.4.1.3 Upwelling contribution from the intervening atmosphere $T_{UP}$

The upward emission by the intervening atmosphere below the aircraft is computed using equation (2.14). The subscript $A/C$ in the rain and atmospheric transmissivities refers to the atmospheric layer below the aircraft. The transmissivity of the rain $\tau_{r,A/C}$ is calculated as follows:

$$\tau_{r,A/C} = e^{-\kappa_r H} \quad (2.22)$$

where $H$ is the altitude of the aircraft.

The transmissivity $\tau_{a,A/C}$ is derived from $\tau_{a,\infty}$:

$$\tau_{a,A/C} = \tau_{a,\infty}^{1-e^{H/x}} \quad (2.23)$$

where $x$ is a quadratic function with empirically determined coefficients from Meissner (2012) [27].
2.4.1.4 Emission from the ocean surface $T_{\text{OCEAN}}$

The emission from the ocean surface $T_{\text{OCEAN}}$ is the main and foremost contributor to the overall observed brightness temperature. It is calculated as follows:

$$T_{\text{OCEAN}} = \varepsilon \cdot \text{SST}$$  \hspace{1cm} (2.24)

where SST is the sea surface temperature and $\varepsilon$ is the emissivity of the ocean surface.

The ocean surface emissivity $\varepsilon$ depends on frequency, SST, salinity and ocean surface wind speed. At C-band it has two parameters:

$$\varepsilon = \varepsilon_0 + \varepsilon_{ws}$$  \hspace{1cm} (2.25)

where $\varepsilon_0$ is the emissivity of the specular ocean surface also known as smooth surface emissivity, and $\varepsilon_{ws}$ is the total excess emissivity due to wind speed.

The specular emissivity $\varepsilon_0$ is given by:

$$\varepsilon_0(f, \text{SST, salinity}) = 1 - |r|^2$$  \hspace{1cm} (2.26)

$$r = \frac{\varepsilon' \cdot \cos(\theta) - \sqrt{\varepsilon'^2 - \sin^2(\theta)}}{\varepsilon' \cdot \cos(\theta) + \sqrt{\varepsilon'^2 - \sin^2(\theta)}}$$  \hspace{1cm} (2.27)

where $r$ is the nadir-incidence Fresnel reflection coefficients for a certain frequency $f$ and incidence angle $\theta$, which for the nadir-looking SFMR is 0 degrees. In (2.27), the variable $\varepsilon'$ denotes the complex dielectric constant of the sea water, based on modeling the frequency dependence through a double Debye relaxation law [28, 27]. Previous SFMR RTM used the nadir-incidence Fresnel reflection coefficients calculated using Klein and Swift algorithm (1977) [29].

The excess emissivity due to wind speed $\varepsilon_{ws} = \varepsilon_{0,ws} + \varepsilon_f$, comprises two components: $\varepsilon_{0,ws}$ solely dependent on the ocean surface wind speed and $\varepsilon_f$, a frequency dependent component [11, 13, 14].
The wind speed dependent term $\varepsilon_{0, ws}$ is a functional form calculated based on a reference frequency channel. Prior RTMs chose the lowest frequency channel available because it is the channel expected to be least impacted by rain. However, the Sapp 2019 RTM argues that this does not completely mitigate non-wind contributions and instead, they use the highest frequency channel given that at lower frequencies, radio frequency interferences (RFI) from other instruments aboard the aircraft are more common. The frequency independent terms is calculated by:

$$
\varepsilon_{0, ws} = \begin{cases} 
a_1 \cdot U_{10N} & U_{10N} < v_1, \\
a_2 + a_3 \cdot U_{10N} + a_4 \cdot U_{10N}^2 & v_1 \geq U_{10} \geq a_0, \\
a_5 + a_6 \cdot U_{10N} & a_0 < U_{10N}
\end{cases}
$$

where $U_{10N}$ is the 10m neutral ocean surface wind speed, measured 10m above the Earth’s surface assuming neutral stability of the atmosphere, which means there is no vertical movement of air parcels [30].

The estimated dropsondes surface wind speed is obtained using layer-averaging techniques, particularly the so-called WL150 algorithm. These measurements are derived from the lowest 150 m thick layer of dropsonde measurements, collected within the range of 10 meters to 350 meters. The average wind speed in this layer is commonly referred to as the WL150 wind. An adjustment is made to estimate the wind speed at an altitude of 10 meters above the Earth’s surface. This adjustment is achieved by applying a scaling factor of 0.85 to the average wind speed. The scaling factor is derived from analyzing layers that are 150 meters thick and positioned at a mean altitude of 85 meters [31, 11, 32, 33]. Under assumed neutral stability of the atmosphere near the surface, the mean wind speed presents a logarithmic profile in relation to the altitude:

$$
U = (U_*/k)\ln(Z/Z_0)
$$

(2.29)
where $U$ is the wind speed, $U_\ast$ is the friction velocity, $k$ is Von Karman constant of $\approx 0.4$, $Z_0$ is the roughness length and $Z$ is the altitude.

The coefficients $a_1$ to $a_6$ in (2.28) are constrained empirically through a function fit utilizing the Levenberg-Marquardt method. Every update to the RTM includes revised coefficients. As for the low breaking point $v_1$, previous RTMs had it set to 7 m/s [2, 11], beyond which wave breaking and the formation of foam are observed [34]. However, Sapp 2019 RTM defines it such as the slope of the quadratic function matches a line that intercepts the origin, usually constrains values around 10.5 m/s. The highest breaking point $a_0$, in previous RTMs was set to 37 m/s via trial and error to minimize the root-mean-square error (RMSE) of the fit, and Sapp 2019 RTM defines it as the point where the upper two curves fit, found to be 54.47 m/s.

The frequency dependent term $\varepsilon_f$ is has a quadratic form and is also empirically determined with revised coefficients, defined as:

$$
\varepsilon_f = (a_7 + a_8 \cdot U_{10N} + a_9 \cdot U_{10N}) \cdot \Delta f
$$

(2.30)

where $\Delta f$ is calculated as the difference between the frequency at which the emissivity is calculated for and the reference frequency, which could be the lowest 4.74 GHz for the previous RTMs [2, 11, 13] or the highest frequency 7.09 GHz for the latest RTM [14].
CHAPTER 3
UMASS SIMULTANEOUS FREQUENCY MICROWAVE RADIOMETER (USFMR)

The UMass SFMR is a Dicke radiometer with 6 parallel frequency channels in C-band from 4.6 GHz to 7.1 GHz with 100MHz of bandwidth per channel. The center frequencies are close to those of the SFMR but not the same.

![Block diagram of the USFMR.](image)

**Figure 3.1.** Block diagram of the USFMR.
The USFMR has dual-polarization capabilities, however, for nadir observations, both polarizations are essentially equal as the electric field is parallel to the surface, and therefore both independent observations are expected to be identical. The dual polarization can be used to improve radiometric precision, $\Delta T$, but this is not part of the scope of this project.

Figure 3.1 shows a block diagram of the USFMR receiver. At the input, a four-port switch can be configured to toggle among four ports: two antenna polarizations (H or V), an ambient temperature load, which acts as a known temperature reference $T_R$, and a calibrated noise source that can be used as a “hot” reference source. Only one of the polarizations is used. The switch allows the USFMR to operate in many different modes such as switching between the antenna and reference ($T_A$-$T_R$), reference and noise source ($T_R$-$T_N$), reference and reference ($T_R$-$T_R$), etc. A band pass filter eliminates out-of-band interferences, and the amplifier chain provides a system gain of around 90 dB. An 8-way power divider splits the signal. Six separate channels are selected by a band pass filter of 100 MHz bandwidth and downconverted to baseband by a diode detector. Following that, a synchronous detector circuit yields a voltage proportional to the difference of the two selected input sources. This voltage is sampled by a multichannel A/D converter, and the raw data counts are stored on an embedded computer.

Originally the system was implemented on a PC104 format embedded computer running Windows95. It consisted of an i386 microprocessor, a multichannel A/D and a Field Programmable Gate Array (FPGA) that controlled the Dicke switch. The FPGA also included provisions for a blanking signal which would force the radiometer to not look at the antenna in the presence of radio frequency interference (RFI), primarily from other radars aboard the aircraft transmitting also at C-band. Table 3.1 shows a detailed list of system specifications. Instabilities in various device drivers rendered the performance of the system marginal and in need of an update. This
chapter outlines all the enhancements and modifications made to the instrument with the intention of bringing it up to date and ready for operation.

<table>
<thead>
<tr>
<th>Center frequencies</th>
<th>4.63, 5.50, 5.92, 6.34, 6.60 and 7.05 GHz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Receiver BW</td>
<td>100 MHz</td>
</tr>
<tr>
<td>Polarization</td>
<td>dual linear</td>
</tr>
<tr>
<td>Antenna</td>
<td>diagonal horn with OMT</td>
</tr>
<tr>
<td>Beamwidth</td>
<td>13°-15°</td>
</tr>
<tr>
<td>Receiver gain</td>
<td>90 dB</td>
</tr>
<tr>
<td>System noise temp.</td>
<td>250-330K</td>
</tr>
<tr>
<td>Radiometric precision</td>
<td>0.1 K</td>
</tr>
</tbody>
</table>

Table 3.1. USFMR specifications

3.1 Embedded system

The original embedded system has undergone a complete overhaul, with a Raspberry Pi 2 now serving as the embedded computer. It operates in conjunction with other compatible daughterboards and an FPGA which are together responsible for data acquisition, signal control and generation and temperature control.

The block diagram in Figure 3.2 illustrates all of the hardware components required for the proper operation of the system. The key elements of this diagram include:

- Raspberry Pi: acts as the brain/center of the system. It runs a Linux operating system.

- ADS 1256: high precision AD/DA Raspberry Pi extension board.

- Temperature board: Adafruit perma-proto breadboard Raspberry Pi extension board, holds the temperature control system and the tinyFPGA.

- tinyFPGA: generates the Dicke clock, the control signals of the 4-port switch and receives the blanking signal.
- Integrator board: custom design PCB board that distributes the control signals of the system and includes the synchronous detector circuit.

![Block diagram of the USFMR embedded system.](image)

**Figure 3.2.** Block diagram of the USFMR embedded system.

The Raspberry Pi is the embedded host and directly communicates with the ADS 1256 board, the tinyFPGA and the temperature sensors installed on the temperature board. All these boards are conveniently stacked on top of the Raspberry Pi. The integrator board not only is used to generate the output voltage of the system that is sampled by the ADS 1256, but it also distributes all the control signals from or to the embedded system, such as the control signals that go to the 4-port switch or the blanking signal received by the tinyFPGA. Although the tinyFPGA is responsible for generating the control signals, the Raspberry Pi serves as a backup signal control generation system in case of a tinyFPGA malfunction, albeit it is unable to handle the blanking signal capability. To switch to the backup signal control generation system, it is necessary to manually switch the cable that connects the Raspberry Pi GPIO pins to the integrator board. In a subsequent section, it will be elaborated on how the
software manages all of this communications. Figure 3.3 shows a picture of the new embedded system. The top layer is the temperature board that houses the FPGA, the temperature sensors and the connectors that interface the integrator board. The temperature sensors are labeled as 1, 2, 3, corresponding to reference load, LNA and noise source, respectively. The red wire headers are connected to the FPGA and the black wire header connected to the GPIO pins to the left, is the backup signal control. The middle layer board is the ADS 1256 multi-channel A/D converter, and the bottom layer is the Raspberry Pi.
### 3.1.1 Raspberry Pi

In this updated system, the Raspberry Pi serves as the central processing unit due to its versatility, cost-effectiveness, portability, and low power consumption. Specifically, a Raspberry Pi 2 model B was selected for its compatibility with numerous products available in the market, which can be conveniently stacked on top of it to enhance its capabilities. Specifications of the board can be found in Table 3.2.

<table>
<thead>
<tr>
<th><strong>Processor chipset</strong></th>
<th>900 MHz quad-core ARM Cortex-A7 CPU</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>RAM</strong></td>
<td>1 GB</td>
</tr>
<tr>
<td><strong>USB 2.0</strong></td>
<td>4 ports</td>
</tr>
<tr>
<td><strong>Ethernet port</strong></td>
<td>yes</td>
</tr>
<tr>
<td><strong>GPIO</strong></td>
<td>40 pins</td>
</tr>
<tr>
<td><strong>Power draw/Voltage</strong></td>
<td>1.8A at 5V</td>
</tr>
<tr>
<td><strong>SD socket</strong></td>
<td>microSD (8GB)</td>
</tr>
</tbody>
</table>

**Table 3.2.** Raspberry Pi 2 model B specifications.

The necessary GPIO pins used to run the radiometer are shown in Figure 3.4, where P1, P2 and P3 are the three pins that communicate the mode selection to the tinyFPGA. The Dicke pin is not used by the Raspberry Pi when the tinyFPGA is working, but it is available to output the Dicke clock when the backup control signal generation system is used. The red labels for V, H, CAL and REF denote the four pins that output the backup control signals for the 4-port switch. The TEMP pin is the one-wire connection to the temperature control sensors, which is further explained in section 3.1.3. The BS pin corresponds to the blanking signal, this pin is connected to both the tinyFPGA and the Raspberry Pi to automatically change to Cal-Ref mode regardless of the previous mode and to communicate to the Raspberry Pi whether the mode has been overwritten, which is then noted in the output data file.

The Raspberry Pi currently supports up to eight distinct operating modes for the USFMR. However, not all of these modes are currently utilized. The following is a list of all available modes:
Figure 3.4. Raspberry Pi2 model B GPIO pins allocation. Red labels denote backup control signals generated directly by the Raspberry Pi.

- **MODE 0**: (Ref/H) Switch between reference load and horizontal polarization. This is currently inoperative due to the absence of horizontal polarization implementation. Nonetheless, it can serve as a backup port in the event of another port malfunction.

- **MODE 1**: (Cal/Ref) This is also referred to as the calibration mode. It switches between the noise source and the reference load.

- **MODE 2**: (Cal/H) Switch between the noise source and the horizontal polarization. This is an inoperative mode.
• MODE 3: (Ref/Ref) This mode solely looks at the reference load. It is used to calculate if there are any offsets in the output voltage.

• MODE 4: (Cal/V) Switch between the noise source and the vertical polarization/antenna. This mode is not used.

• MODE 5: (TPR V) This mode only looks at the antenna port. This mode is not used.

• MODE 6: (Ref/V) Switch between reference load and vertical polarization/antenna. This is the primary operational mode of the USFMR.

• MODE 7: (V/Ref) Switch between vertical polarization and reference load. This mode is never used given that the measured voltage of the reference load is greater than the one measured from the antenna.

In essence, the 4-port switch utilizes two distinct ports that are alternated according to the Dicke clock. The resulting output voltage is obtained by the synchronous detector circuit, which calculates the difference between the two ports.
3.1.2 FPGA

The signal control of the system is carried out by a combination of an FPGA and a Raspberry Pi. The chosen FPGA manufacturer was TinyFPGA, a crowd funded company that makes a series of low-cost, open source, user friendly FPGAs. For the purposes of this project, the chosen FPGA model was the tinyFPGA BX board. It uses Lattice Semiconductor’s iCE40 FPGA, which incorporates an easy access programming interface through a micro-USB port. It supports both Lattice development environments and an open-source IceStorm FPGA toolchain. This makes FPGA programming accessible to inexperienced users with tools such as IceStudio, a visual editor and programmer for open FPGA boards through the use of graphical schematics, so the user can configure the FPGA without previous knowledge of VHDL. TinyFPGA requires Python & Apio, which is is a multi platform toolbox, with static pre-built packages, project configuration tools and easy command interface to verify, synthesize, simulate and upload verilog designs.

Figure 3.5. Image of the TinyFPGA BX. (sourced from www.sparkfun.com)

Figure 3.5 shows a picture of the TinyFPGA BX and Table 3.3 shows the specifications table of the board. The FPGA drives the Dicke clock signal, this is generated by using the internal microelectromechanical (MEM) oscillator that operates at 16 MHz and by the means of a clock divider it is scaled down to 980 Hz. The FPGA also generates the control signals that drive the 4-port switch (V, H, REF and CAL)
and receives the blanking signal, which triggers the USFMR to switch its mode to Cal/Ref from its previous mode.

<table>
<thead>
<tr>
<th>FPGA CHIP</th>
<th>ICE40LP8K</th>
</tr>
</thead>
<tbody>
<tr>
<td>Programming interface</td>
<td>USB 2.0</td>
</tr>
<tr>
<td>Logic cells</td>
<td>7680</td>
</tr>
<tr>
<td>Block RAM</td>
<td>128 KBit</td>
</tr>
<tr>
<td>SPI flash</td>
<td>8 MBit</td>
</tr>
<tr>
<td>Phase lock loops</td>
<td>1</td>
</tr>
<tr>
<td>LDO regulators</td>
<td>3.3V &amp; 1.2V</td>
</tr>
<tr>
<td>MEMs oscillator</td>
<td>16MHz</td>
</tr>
<tr>
<td>User IO pins dedicated</td>
<td>31</td>
</tr>
<tr>
<td>User IO pins shared</td>
<td>10</td>
</tr>
</tbody>
</table>

**Table 3.3.** TinyFPGA BX specifications.

Out of all the available pins on the tinyFPGA, 5 output pins are required to send out the control signals of the 4-port switch (vertical V, horizontal H, noise source CAL and reference load REF) and the Dicke clock, and 4 input pins to receive P1, P2, P3 signals from the Raspberry Pi, to determine which mode does the user want to implement and the blanking signal (BS). Table 3.4 lists all the specific pins employed in this process.

<table>
<thead>
<tr>
<th>NAME</th>
<th>I/O</th>
<th>PIN</th>
</tr>
</thead>
<tbody>
<tr>
<td>vs signal</td>
<td>O</td>
<td>13</td>
</tr>
<tr>
<td>H signal</td>
<td>O</td>
<td>12</td>
</tr>
<tr>
<td>REF signal</td>
<td>O</td>
<td>11</td>
</tr>
<tr>
<td>CAL signal</td>
<td>O</td>
<td>10</td>
</tr>
<tr>
<td>Dicke</td>
<td>O</td>
<td>9</td>
</tr>
<tr>
<td>P1</td>
<td>I</td>
<td>1</td>
</tr>
<tr>
<td>P2</td>
<td>I</td>
<td>2</td>
</tr>
<tr>
<td>P3</td>
<td>I</td>
<td>3</td>
</tr>
<tr>
<td>Blanking signal</td>
<td>I</td>
<td>4</td>
</tr>
<tr>
<td>GND</td>
<td>-</td>
<td>6 &amp; 8</td>
</tr>
</tbody>
</table>

**Table 3.4.** Pinout table for the FPGA

The user operating the instrument can manually set the operational mode of the instrument through the Raspberry Pi. As previously discussed in Section 3.1.1, the
instrument can operate under 8 distinct set-ups. For each mode, each port of the switch must receive a unique control signal to determine the state of that particular port. Consequently, the FPGA must generate different control signals corresponding to the specific operational mode being implemented. The 4-port switch expects one out of four different control signals: a 1 or high, which indicates that the corresponding port is closed; a 0 or a low, which indicates that the port is open; or a pulse, which can also be a reverse pulse, resulting in the port alternating between open and closed states in accordance with the pulse signal received. The FPGA design to select the operational mode is divided in three different stages. The first stage receives three different signals from the Raspberry Pi (P1, P2, P3), resulting in eight different combinations, one for each mode available. The second stage is to generate all the output signals that controls the 4-port switch. Tables 3.5 and 3.6 are the corresponding truth tables of the first and second stage of the FPGA design, respectively. The third stage is required to overwrite the mode selected by the user to Cal/Ref if the blanking signal is activated.

<table>
<thead>
<tr>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>num.</th>
<th>MODE</th>
<th>S1</th>
<th>S2</th>
<th>S1</th>
<th>S2</th>
<th>S1</th>
<th>S2</th>
<th>S1</th>
<th>S2</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>Ref/H</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>Cal/Ref</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>Cal/H</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>Ref/Ref</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>Cal/V</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>5</td>
<td>TPR V</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>6</td>
<td>Ref/V</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>7</td>
<td>V/Ref</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 3.5. Modes truth table.
<table>
<thead>
<tr>
<th>S1</th>
<th>S2</th>
<th>OUT</th>
<th>SIGNAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>i1</td>
<td>pulse</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>i3</td>
<td>0 (low)</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>i2</td>
<td>reverse pulse</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>i4</td>
<td>1 (high)</td>
</tr>
</tbody>
</table>

Table 3.6. Sel1 and sel2 table.

Figure 3.6. FPGA logic circuit.
The block diagram of the FPGA circuit is depicted in Figure 3.6, which comprises three distinct stages and four input signals, namely P1, P2, P3, and BSignal. In the first stage, the three input signals are divided into four pathways, one for each port of the switch. This stage involves four different logic circuits that generate two output values, S1 and S2, which serve as the selection lines for the four 4:1 multiplexers in the second stage. The inputs of these multiplexers are the four different signals used to control the 4-port switch. The third stage consists of 2:1 multiplexers that overwrite the output of the second stage in the presence of a blanking signal.

For detailed information on the specific digital circuits involved in each stage, please refer to the Appendix.
3.1.3 Temperature control system

The temperature control and monitoring system is a vital part of the instrument as radiometers are highly sensitive to temperature fluctuations. Correct measurements of the physical temperature of the instrument is essential to the retrieval of accurate data. The system upgrades are solely focused on the monitoring system as the temperature control continues to employ the old system, flexible polyimide heater plate pads controlled by an independent temperature controller. This controller is manually set to a specific temperature and regulates the heating pads as required.

Regarding the monitoring system, a simple yet efficient design compatible with the Raspberry Pi was chosen. This design incorporates DS18B20 programmable resolution 1-wire digital thermometers. Currently, the system features three different sensors, dedicated to the noise source, the reference load and the low noise amplifier. It was decided to use digital temperature sensors over analog because of their higher accuracy, 12-bit at 0.0625°C of resolution. They are user-friendly, as they do not require external circuitry and can be directly connected to a microcontroller or a computer via a 1-wire connection. Furthermore, their discrete nature makes them less susceptible to noise and interferences. The wiring of the system is enclosed on an Adafruit perma-proto HAT that connects directly to the GPIO pins of the Raspberry Pi.
3.1.4 Integrator board

The integrator board houses the synchronous detector circuit (SDC), which generates a voltage proportional to the difference between the selected ports, typically the antenna and the reference load. Furthermore, the integrator board facilitates the transmission of control signals from the embedded system to the downconverter through SMB connectors.

The original integrator board was refurbished after incurring damage and utilized during the 2019 hurricane season. However, it subsequently failed, necessitating a replacement. Given the absence of any previous documentation or schematics of the board, it was necessary to reverse engineer the original circuit to comprehend its functioning. Additionally, the SDC was divided across two layers in the original board, resulting in a suboptimal design. The prior board also featured several connections that were a part of the old embedded system and were no longer relevant for the new system. As a result, those components were eliminated. The new integrator board replicates the SDC from the original board.

![Block diagram of integrator board circuit.](image)

**Figure 3.7.** Block diagram of integrator board circuit.
The block diagram of the SDC is shown in Figure 3.7. This only depicts one of the six channels, this circuit is replicated for each of the channels. The circuit serves as an amplification stage, and is comprised of low power monolithic amplifiers (OP848). Subsequently, a monolithic CMOS analog multiplexer (ADG409) directs the signal to the different inputs of the differential amplifier (AD620) in accordance with the Dicke clock. For example, in the event of measuring Ref/V, the signal from the reference load is directed towards the positive input of the amplifier while the antenna measurement is fed to the negative input. Prior to the differential amplifier there is an RC low pass filter to reject any high-frequency noise. The cut-off frequency is approximately 20 Hz. Table 3.7 lists the values of all the resistors and capacitors of the SDC.

<table>
<thead>
<tr>
<th>NAME</th>
<th>CH1</th>
<th>CH2</th>
<th>CH3</th>
<th>CH4</th>
<th>CH5</th>
<th>CH6</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>1kΩ</td>
<td>1kΩ</td>
<td>1kΩ</td>
<td>1kΩ</td>
<td>1kΩ</td>
<td>1kΩ</td>
</tr>
<tr>
<td>R2</td>
<td>10kΩ</td>
<td>10kΩ</td>
<td>10kΩ</td>
<td>10kΩ</td>
<td>10kΩ</td>
<td>10kΩ</td>
</tr>
<tr>
<td>R3</td>
<td>49kΩ</td>
<td>49kΩ</td>
<td>49kΩ</td>
<td>49kΩ</td>
<td>49kΩ</td>
<td>49kΩ</td>
</tr>
<tr>
<td>R4</td>
<td>1kΩ</td>
<td>1kΩ</td>
<td>1kΩ</td>
<td>1kΩ</td>
<td>1kΩ</td>
<td>1kΩ</td>
</tr>
<tr>
<td>R5</td>
<td>34kΩ</td>
<td>23kΩ</td>
<td>34kΩ</td>
<td>21kΩ</td>
<td>28kΩ</td>
<td>28kΩ</td>
</tr>
<tr>
<td>R6</td>
<td>73kΩ</td>
<td>73kΩ</td>
<td>73kΩ</td>
<td>73kΩ</td>
<td>73kΩ</td>
<td>73kΩ</td>
</tr>
<tr>
<td>R7</td>
<td>73kΩ</td>
<td>73kΩ</td>
<td>73kΩ</td>
<td>73kΩ</td>
<td>73kΩ</td>
<td>73kΩ</td>
</tr>
<tr>
<td>R8</td>
<td>24kΩ</td>
<td>28kΩ</td>
<td>66kΩ</td>
<td>14kΩ</td>
<td>24kΩ</td>
<td>14kΩ</td>
</tr>
<tr>
<td>C1</td>
<td>0.1μF</td>
<td>0.1μF</td>
<td>0.1μF</td>
<td>0.1μF</td>
<td>0.1μF</td>
<td>0.1μF</td>
</tr>
<tr>
<td>C2</td>
<td>0.1μF</td>
<td>0.1μF</td>
<td>0.1μF</td>
<td>0.1μF</td>
<td>0.1μF</td>
<td>0.1μF</td>
</tr>
</tbody>
</table>

Table 3.7. Specifications table of the block diagram circuit

Complete layouts of the new integrator board can be found in the Appendix. Figure 3.8 shows a picture of the new integrator board printed and prior to PCB assembly.
Figure 3.8. New integrator board prior to PCB assembly.
3.1.5 Software

The software implementation of the system comprises two distinct components: one that governs the instrument’s functionality and another that communicates with the instrument via a UDP connection from the user’s computer. Figure 3.9 presents a block diagram of the primary executables involved in this process. Each segment is enclosed within a dashed line box, and the two main programs, which operate on both the user’s laptop and the embedded system within the instrument, are highlighted in green. On the instrument’s side, usfmr.c serves as the primary executable responsible for managing the instrument’s operations. The user can connect to the Raspberry Pi via secure shell (ssh) and execute the program to specify the desired mode of operation. The thick double-ended arrows depict parallel threads that handle temperature sensors (temp.c), and the control signals for the tinyFPGA or the backup control signal generation (dicke.c). The primary executable also calls ads1256.c which han-
dles the ADC. The data collected is then stored in an ASCII file. Figure 3.10 shows an example of the content and structure of a raw binary file. The file comprises 11 columns, with the first column indicating time in epoch UNIX timestamp format. The following three columns indicate temperature sensors readings reported in Celsius. The fourth column denotes the selected mode, while the final six columns record the counts for each frequency channel, arranged from the lowest to the highest frequency.

| 1560954863.409 | 32.312 | 32.625 | 32.062 | 6 | 19189 | 19446 | 3660 | 16922 | 18994 | 16329 |
| 1560954863.422 | 32.312 | 32.625 | 32.062 | 6 | 19367 | 19458 | 3662 | 16914 | 18970 | 16402 |
| 1560954863.434 | 32.312 | 32.625 | 32.062 | 6 | 19306 | 19617 | 3751 | 17134 | 19197 | 16615 |
| 1560954863.446 | 32.312 | 32.625 | 32.062 | 6 | 19243 | 19603 | 3706 | 17103 | 19150 | 16514 |
| 1560954863.458 | 32.312 | 32.625 | 32.062 | 6 | 19238 | 19547 | 3691 | 17036 | 19074 | 16385 |
| 1560954863.471 | 32.312 | 32.625 | 32.062 | 6 | 19190 | 19566 | 3680 | 17041 | 19060 | 16425 |

Figure 3.10. Example of a raw data file generated by the USFMR measurements (2019/06/12).

The usfmr.c executable offers various modes of operation that can be executed by providing specific command line arguments. The user has the ability to specify the desired mode, configure the auto-calibration interval, and determine the frequency, measured in seconds, at which the calibration should occur. Additionally, the user can opt to generate an output file containing the collected data. Near-real-time data visualization is also available on the user’s laptop with the option to broadcast the collected data through a UDP socket.

On the laptop’s end, the user has the option to run a bash file, sync_file, to transfer the raw binary files from the Raspberry Pi to the laptop automatically. Additionally, the user can execute remote.c to process the raw data, in counts, and obtain processed files that provide brightness temperatures. The format of the processed file is identical to that of the raw data file, except that the last six columns contain brightness temperatures in Kelvin. Moreover, the user’s laptop is linked to the aircraft’s main broadcast stream, enabling it to access information being broadcasted, such as navigation data. The executable nav.c reads in the data and stores it in a log file.
3.2 Calibration

Calibration of the radiometer is essential to obtain accurate results. Radiometers are highly affected by temperature fluctuations potentially affecting the receivers response. The system itself also introduces noise that, in theory, could be quantified by knowing the specifications of all its components. Although, this scenario would be an ideal one, in practical applications such determinations are often more complex, requiring a calibration protocol to establish the connection between the input brightness temperature and the output quantity of the radiometer, in volts or digital counts. As discussed in Chapter 2, the output voltage of a Dicke radiometer is equivalent to

\[ V_{\text{out}} = \text{constant} \cdot (T_A - T_R) \]

where \( T_R \) is known and only the multiplying constant needs to be determined. The input-output relationship can be established with one point calibration assuming the radiometer is perfectly linear.

There are multiple methods for calibrating a radiometer, the most commonly used include, using a noise source as the hot source, a cryogenically cooled microwave load or cooled targets such as microwave absorbers, or sky calibration, where observations of the sky are used instead of a cooled target. In this project, a sky calibration is used. Sky calibration is a very effective methodology, especially for frequencies between 1-10 GHz, where the cold sky temperature is relatively undisturbed by the atmosphere and known to be approximately 6K [19]. This calibration is usually performed by pointing the radiometer to the sky from the inside of a large metal bucket to insure that the radiometer is only measuring sky radiation. In this case, a metal bucket was not available and so the measurements were taken in a local parking lot, which is surrounded by other buildings that may have potentially influenced the results. Nevertheless, the Dicke radiometer only requires one point calibration and there were two available, the sky calibration and the noise source. It was decided to use both to eliminate any uncertainty in the measurements caused by nearby building radiation. In addition, a mode 3 Ref/Ref, measuring the reference load exclusively, in order
to compute any DC offsets was employed. This is accomplished by utilizing the equation \( V_{out} = constant \cdot (T_R - T_R) = 0V \), thereby facilitating the identification of any deviations. The new output voltage would be \( V_{out} = constant \cdot (T_A - T_R) + b \), where \( b \) is the offset. Both the constant and the offset \( b \) can be calculated with the instrument installed on the aircraft given that it does not require to measure anything through the antenna, however, it is recommended to still perform the sky calibration procedure prior to the installation of the instrument on the aircraft.

![Figure 3.11](image)

**Figure 3.11.** Brightness temperature (K) versus output voltage (V) from hot and cold USFMR calibration procedure performed June 12\(^{th}\) 2019.

<table>
<thead>
<tr>
<th>Frequency (GHz)</th>
<th>slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.63</td>
<td>0.0179830</td>
</tr>
<tr>
<td>5.50</td>
<td>0.0220727</td>
</tr>
<tr>
<td>6.34</td>
<td>0.0191156</td>
</tr>
<tr>
<td>6.60</td>
<td>0.0192900</td>
</tr>
<tr>
<td>7.05</td>
<td>0.0128761</td>
</tr>
</tbody>
</table>

**Table 3.8.** Coefficients from the hot and cold calibration procedure from June 12\(^{th}\) 2019.

Figure 3.11 shows the hot and cold calibration procedure performed on June 12\(^{th}\) 2019, using the sky as the cold source and the noise source as the hot source.
Frequency channel 5.92 GHz had hardware damage during this calibration procedure so it is not included in the figure. Table 3.8 presents the slope obtained from each channel.
CHAPTER 4
HURRICANE LORENZO 2019

The USFMR flew alongside the operational SFMR aboard the N43RF NOAA WP-3D aircraft through hurricane Lorenzo during September 28th and 29th of 2019. The data collected during this mission has been utilized to conduct a comparative analysis of the performance of both instruments, with the aim of evaluating any discernible disparities between them.

Lorenzo was the second deadliest hurricane in the 2019 season, after hurricane Dorian, and one of the strongest hurricanes on record to travel farther east and north in the Atlantic ocean. It formed off the west coast of Africa on September 22nd, it moved westward before reaching its peak category and then redirected toward Europe losing its tropical cyclone conditions when it reached the Azores on October 1st 2019 [35].

Figure 4.1 shows the best track positions of Lorenzo as well as its respective categories throughout its lifespan. During its highest state, NOAA deployed two NOAA P-3 Hurricane Hunter aircrafts and the NOAA G-IV jet for a total of six research missions in and around the hurricane. The N43RF was originally planned to fly through the hurricane in 3 separate missions. However, the first one, which was scheduled for September 27th, was cancelled because the P-3 aircraft was diverted to support a search and rescue operation after the vessel Bourbon Rhode sank close by on September 26th. The second mission was conducted on September 28th. It was a science mission directed by the NOAA/NESDIS/STAR science team. The primary goal was to target regions with high-gradient winds. The third and last mission took place
Figure 4.1. Best track positions for hurricane Lorenzo from September 23rd to October 2nd (Figure 1 from NHC tropical cyclone report [35]). The different colors on the track path denote the category of the hurricane and the black arrow highlights its peak wind speed location.

on September 29th, a joint storm reconnaissance mission with the N42RF aircraft. The main purpose was to locate the center of the storm and measure central pressure and surface winds around the eye. The evaluation of the instruments performance is based on the data collected during the second mission, as it had more penetrations than the third mission and thus, more useful information. The key difference between the SFMR and the USFMR is the sampling methodology. The SFMR samples sequentially through the different frequency channels, requiring roughly 10 seconds to complete a full measurement. Conversely, the USFMR samples all frequency channels simultaneously, obtaining a complete, independent sample every second.
Figure 4.2. Flight path of N43RF aircraft on September 28th 2019 through hurricane Lorenzo (top). The dash purple circle denotes an approximation of the hurricane’s eye location for visual purposes. X and Y axes are latitude and longitude in degrees, respectively. USFMR lowest frequency channel brightness temperature \( T_B \) measurement that matches the flight path depicted on the top plot (bottom). The X axis is time in seconds relative to the flight path and Y axis is \( T_B \) in Kelvin. The different colors highlight inbound and outbound passes of the eye-wall.

Figure 4.2 shows two different plots. The upper plot shows the flight path of the N43RF aircraft, and the lower plot shows the matching \( T_B \) for the lowest frequency channel of the USFMR. This figure showcases a flight where the main goal was to target high wind-gradient regions of the eye-wall, resulting into a flight pattern similar to the petals of a flower, which falls under the synoptic missions category, where targeting the center of the storm is not the objective. Every mission has a prescribed flight-time in the hurricane area, and the goal in this particular mission was to conduct as many passes, or penetrations, of the eye-wall as possible. In this case, a total of six passes were completed, three inbound and three outbound. The various colors used in
both plots indicate different passes through the eye-wall. As reflected by the bottom plot displaying the measured brightness temperature ($T_B$), there are eight discernible peaks, each representing an individual pass through the eye-wall. The initial and final peaks are not color-highlighted due to their relatively lower intensity, given that the hurricane did not feature a completely formed and enclosed eye-wall, and therefore those lower intensity areas were picked as the first entrance and final exit of the center of the storm. The brightness temperature measurement has a very discernible pattern where $T_B$ rapidly increases reaching notably high values, followed by a steep decline. These peaks and valleys represent the eye-wall and the center of the eye, respectively. The eye-wall of a hurricane is composed of intense thunderstorm with winds that can reach up to 90 m/s and heavy rainfall, whereas the eye of a hurricane is the calm center of the storm. The primary focus of this work are the high peaks where the highest winds are present.

4.1 Brightness temperature comparison

The first step to compare and contrast the performance of the two instruments is to look at the observed brightness temperatures.

![Figure 4.3](image)

**Figure 4.3.** Brightness temperature measured with the lowest frequency channel available in Kelvins as a function of time in seconds. Red and cyan represent OP SFMR (4.74 GHz) and USFMR (4.63 GHz) measured $T_B$, respectively.

Figure 4.3 illustrates the $T_B$ measured with the lowest frequency channel available in each instrument, synchronized in time. The OP SFMR data represented in red
(4.74 GHz) and blue for the USFMR (4.63 GHz). While the two data sets match quite well, note that the USFMR data appears initially to be lower than the OP data. However, it eventually increases and the two data sets match quite closely for the duration of the hurricane passes and then it diverges again at the end of the record. This $T_B$ drift can be observed in all of the frequency channels. For this plot the RMSE is 7.53 K and the average bias is 6.33 K. The root-mean-square error (RMSE) is defined as the square root of the mean squared difference of the two data sets.

After a thorough inspection of all the factors that could potentially impact this bias, it was discovered that the USFMR temperature control was not maintaining the optimum temperature inside the instrument box in the presence of changes in the flight-level air temperature caused by changes in aircraft altitude.

Figure 4.4. Brightness temperature difference between OP SFMR and USFMR for the lowest frequency channels ($T_{BSFMR} - T_{BUSFMR}$) as a function of time in seconds (top). Temperature inside the USFMR box measured by a temperature sensor, expressed in Celsius, as a function of time in seconds (bottom).
It can notice in Figure 4.4 that the difference between the observed $T_B$ by the OP SFMR minus the USFMR $T_B$(top) is inversely proportional to the temperature measured by one of the temperature sensors located inside the USFMR instrument box (bottom). By getting a polynomial fit to this curve and subtracting it from the data, the $T_B$ bias in the USFMR measurement can be minimized. This process is repeated for each of the different frequency channels.

![Graph of brightness temperature measured with the lowest frequency channel available in Kelvins as a function of time in seconds. Red represents $T_B$ measured by OP SFMR (4.74 GHz) and green depicts $T_B$ measured by USFMR (4.63 GHz) with temperature correction.](image)

**Figure 4.5.** Brightness temperature measured with the lowest frequency channel available in Kelvins as a function of time in seconds. Red represents $T_B$ measured by OP SFMR (4.74 GHz) and green depicts $T_B$ measured by USFMR (4.63 GHz) with temperature correction.

Once the temperature trend correction is applied to the USFMR $T_B$ measurements, the data sets show a higher degree of agreement. The impact of the correction can be observed in Figure 4.5. Now the RMSE is 3.19 K and the averaged bias is reduced to 1.09 K.

To visually appreciate the difference between sequential and simultaneous sampling methods, a smaller time scale is needed. Figure 4.6 displays two zoomed plots of the measured $T_B$ with the lowest available frequency channels for the third inbound pass of the eye-wall, of both the OP SFMR (red for 4.74 GHz) and the USFMR (black for 4.63 GHz). The OP SFMR measurement is offset by +5 K for visual purposes. Also highlighted in the plot are the samples in time when the OP SFMR obtains a new measurement for that particular channel (blue). For reference, marked in green, the USFMR sample that matches with the updated sample of the OP SFMR. Upon
Figure 4.6. Zoomed views of measured $T_B$ of inbound penetration of the hurricane eye wall for lowest frequency channel (OP USFMR offset by 5K for visual purposes). USFMR $T_B$ in black. OP SFMR in red and highlighted in blue to new measurements that get replicated while the channel remains idle. The green highlights in the USFMR data when does the OP SFMR update. X axis is time in seconds relative the full hurricane flight (Figure 4.5). Y axis represents $T_B$ in Kelvin.

Examining the OP SFMR data, it is easily noticeable a distinct staircase pattern, which is a consequence of sequential sampling. With this method, the inactive channels remain idle while others update, leading to a less uniform data set, where only 27.3% of the channel data are new samples. Conversely, the USFMR updates all the channels simultaneously to obtain an updated value for all channels every second. So, even though the $T_B$ measurements from both instruments are very similar, it is noticeable that the OP SFMR exhibits a smoothed representation of areas with dips and peaks, whereas the USFMR provides observations with greater fidelity, preserving finer-scale details.
4.2 Retrieved rain rate and wind speed

The accurate retrieval of wind speed and rain rate of hurricanes is essential for numerous reasons including forecasting, disaster management, climate research and so on. In this section results of the retrieval are shown and compared of both the OP SFMR and the USFMR implementing the retrieval algorithm which called in this study NOAA 2019 or Sapp 2019 RTM [14] using the measured $T_B$s studied in the prior section. It is anticipated that the eye-wall of the hurricane will exhibit higher wind speeds and rain rates as shown in Figure 4.7. These plots display the wind speed in m/s (top) and the rain rate in mm/hr (bottom) retrieved with both instruments for the entire hurricane flight. It can be noted that the regions with higher values correspond to the eye-wall crossing of the hurricane. The eye exhibits close to no rain and very low wind speeds, as expected. The maximum measured wind speeds are up to 60 m/s making the hurricane at this particular time a Category 4 major hurricane, according to the Saffir-Simpson hurricane wind scale, which categorizes hurricanes based on the measured sustained winds. Category 4 hurricanes include wind speeds from 58 m/s to 70 m/s [36].

To comprehensively evaluate and contrast the results of both instruments data from Figure 4.7 is analyzed in the time domain, with scatter plots and zoomed in plots for different eye-wall passes, and in the frequency domain, calculating the power spectrum.

4.2.1 Time domain

Figure 4.8 depicts two scatter plots where the X axes correspond to OP SFMR data and the Y axes to the USFMR for wind speed (left) and rain rate (right), in m/s and mm/hr, respectively. The green points correspond to OP SFMR data retrieved with $T_B$s smoothed with a boxcar average of 10 samples, whereas the black data shows the OP SFMR retrievals without any $T_B$ smoothing. It is discernible that the
Figure 4.7. Retrieved wind speed (top) and rain rate (bottom) for the whole hurricane flight. OP SFMR retrievals are shown in black and USFMR in red. X axis represents time in seconds and Y axes units are m/s (top) and mm/hr (bottom).

OP SFMR retrievals (both filtered and unfiltered) demonstrate slightly higher wind speeds than those of the USFMR, however, in the case of rain rate, the results are inverted, where the USFMR exhibits higher rain rates.

<table>
<thead>
<tr>
<th></th>
<th>BIAS</th>
<th>BIAS (S)</th>
<th>RMSE</th>
<th>RMSE (S)</th>
</tr>
</thead>
<tbody>
<tr>
<td>WS (m/s)</td>
<td>2.98</td>
<td>2.52</td>
<td>5.35</td>
<td>5.02</td>
</tr>
<tr>
<td>RR (mm/hr)</td>
<td>-0.49</td>
<td>-0.43</td>
<td>1.84</td>
<td>1.69</td>
</tr>
</tbody>
</table>

Table 4.1. Calculated bias & RMSE from Figure 4.8. (S) denotes OP SFMR data set smoothed (averaged).

Table 4.1 shows the calculated biases between the OP SFMR retrievals and the USFMR for both OP SFMR data sets, averaged and not averaged. It can be appreciate that both the bias and the RMSE is lower when averaging the OP SFMR data.

To effectively observe the difference in the retrievals between the two instruments, it is essential to focus the attention on a specific area of interest, such as the crossings of the eye-wall. Figure 4.9 shows a compilation of plots that depict retrieved wind
Figure 4.8. Scatter plot OP SFMR retrievals versus USFMR retrievals for wind speed (left) and rain rate (right). The green dots show OP SFMR retrievals obtained with $T_B$s averaged with a 10 sample window and black without averaging. Units are m/s (left) and mm/hr (right).

speed, in m/s, and rain rate, in mm/hr, for two different penetrations of the eye-wall as a function of time in seconds, for the USFMR (black for rain rate, green for wind speed) and the OP SFMR averaged (right) and not averaged (left) (red for rain rate, blue for wind speed). For comparison purposes, also shown are the scatter plots below the time-series plots for OP SFMR versus USFMR (left-rain rate, right-wind speed) for both OP SFMR data averaged (green) and not averaged (black). Similar to Figure 4.6, it can observed from the time-series plots in the 1st & 3rd rows, that the USFMR data presents higher detail in fine-scale features for both wind speed and rain rate. Regarding the OP SFMR, it can be appreciated that the average data appears to be less noisy. The official data used by NOAA and the Air Force is always filtered. By looking at the scatter plots it can be noticed the same bias behavior seen in Figure 4.8, where the OP SFMR seems to retrieve slightly higher wind speeds but the USFMR retrieves higher rain rates.
Figure 4.9. Zoomed view of retrieved wind speed in m/s (blue-OP SFMR, green-USFMR) and rain rate in mm/hr (red-OP SFMR, black-USFMR) over time in seconds of two different eye-wall passes ($1^{st}$ & $3^{rd}$ row) for OP SFMR averaged (right column) and not averaged (left column). The $2^{nd}$ & $4^{th}$ row show corresponding scatter plots for rain rate (left) and wind speed (right) comparing averaging effect over the OP SFMR versus USFMR retrievals (green is averaging, black is without).
<table>
<thead>
<tr>
<th></th>
<th>BIAS (m/s) - 2&lt;sup&gt;nd&lt;/sup&gt; row</th>
<th>BIAS (S)</th>
<th>RMSE</th>
<th>RMSE (S)</th>
</tr>
</thead>
<tbody>
<tr>
<td>WS (m/s)</td>
<td>2.02</td>
<td>1.61</td>
<td>4.27</td>
<td>3.01</td>
</tr>
<tr>
<td>WS (m/s)</td>
<td>1.98</td>
<td>1.48</td>
<td>5.07</td>
<td>3.44</td>
</tr>
<tr>
<td>RR (mm/hr)</td>
<td>-1.02</td>
<td>-0.94</td>
<td>2.61</td>
<td>1.78</td>
</tr>
<tr>
<td>RR (mm/hr)</td>
<td>-1.57</td>
<td>-1.37</td>
<td>3.43</td>
<td>2.04</td>
</tr>
</tbody>
</table>

**Table 4.2.** Calculated bias & RMSE from Figure 4.9 scatter plots. (S) denotes OP SFMR data set smoothed (averaged).

Table 4.2 shows similar results, where the averaged OP SFMR data presents less bias and RMSE when compared to the USFMR data.

The retrieval discrepancy between the two instruments can be attributed to many factors. However, after conducting different analysis on the performance of the USFMR, post-season, defective noise diode detectors were found that directly affects the performance of the USFMR, which could have been damaged during the shipping of the instrument, as well as the already noted physical temperature control issues which also directly highly affect the measurements. As a result, this study has concluded that the retrievals obtained with the USFMR, although very promising in regards to capturing higher detail of smaller scale features, it is necessary to further work on the calibration process of the instrument. All the damaged hardware has been replaced afterwards, however, the USFMR has not had another opportunity to fly and test its performance.

### 4.2.2 Frequency domain

The study of the variance spectrum of a signal is a commonly employed technique in studies of turbulence in the atmosphere to observe features over a wide range of scales. The power spectrum at low frequencies, indicate that the storm is dominated by slow-moving, large-scale features. The spectrum then decreases in power as frequency increases, indicating that the storm’s wind field contains smaller-scale features [37].
Figure 4.10. Variance spectrum in logarithmic scale of SFMR retrieved wind speed (left) and rain rate (right) of the whole hurricane flight. Black denotes retrievals obtained with the OP SFMR without averaging $T_B$. Green shows the OP SFMR retrievals with $T_B$ averaged over 10 samples and red is the USFMR retrieved data.

Figure 4.10 shows the power spectrum of Figure 4.7 with both axes in a logarithmic scale for wind speed (left) and rain rate (right), sampling rate 1Hz. The black line corresponds to OP SFMR data without any averaging over the $T_B$s, green is OP SFMR with averaging and red is the USFMR data. The plots indicate that the USFMR data exhibits higher levels of energy in the higher frequencies. The spikes that appear in the wind speed plot (left), for the OP SFMR data (not smoothed), are attributed to the stepping methodology employed by the SFMR. Smoothing the data eliminates these spikes however it also leads to a reduction in the sensitivity to smaller scale features. This effect is particularly pronounced in the wind speed measurements, compared to the rain rate, because the rain rate is typically observed in bands or episodes, whereas the wind is mostly present everywhere. These observations confirms that the USFMR has a superior ability to capture fine-scale details in comparison to the OP SFMR, which for example, could provide valuable information in the studies of structure and dynamics of hurricanes.
CHAPTER 5

WINTER-TIME RETRIEVAL REFINEMENT FOR THE STEPPED FREQUENCY MICROWAVE RADIOMETER

The objective of this chapter is to use available historical data from prior NOAA winter missions, which took place in Ireland, Canada, and Alaska (USA). The purpose of those missions was to identify the source of the error that results in the SFMR retrievals indicating extremely high rain rates for days that have been reported to have light rain or even no rain present. All the data used in this chapter has been provided by NOAA/NESDIS/STAR. The inconsistencies that appear in the SFMR data in extra tropical cyclones (ETCs) can be attributed to various factors. Major differences that are encountered in winter-time extra-tropical conditions are significantly lower ambient temperatures, lower freezing level height ($H_r$), and lower sea surface temperatures when compared to tropical cyclones conditions. This chapter presents different hypotheses that attempt to explain and to mitigate the inconsistencies currently found in the retrievals.

Figure 5.1 shows an example of retrievals obtained during the NOAA Ocean Winds winter mission 2021 based out of Anchorage (AK), USA. For this specific interval of the flight, $H_r$ varies from negative values to approximately 300 m. The plot shows retrieved rain rate in mm/hr (black) and wind speed in m/s (red) for an interval of the flight beginning at 18:32:03 UTC on February 28th 2021. The science crew aboard the aircraft reported very little to no rain present, yet the retrieval produces extremely high rain rate values. Although the retrieved wind speed appears to be uninfluenced, the coupled nature between wind speed and rain rate within the retrieval algorithm means that the erroneous rain rate likely impacts the wind retrieval as well. To
address this issue and to correct the retrieval, this study aims to modify the RTM equations and tailor them to the specific environment in which the SFMR is operating.

As previously explained in Chapter 2, the retrieval algorithm employs the radiative transfer model (RTM) to determine the brightness temperature that would result from the given input parameters, such as wind speed, rain rate, ambient temperature, SST and so on. The RTM needs to offers an accurate representation of the environment where the measurements are obtained; otherwise, the retrievals will be inherently inaccurate. Based on the current RTM, the expected $T_B$ as a function of wind speed or rain rate can be observed in Figure 5.2. This figure compares modeled $T_B(WS)$ and $T_B(RR)$ for different environments. The solid lines illustrate the brightness temperatures for typical tropical cyclone environment with the following parameters: aircraft altitude of 2000 m, SST of 28°C, salinity of 36 psu, and $H_r$ of 4000 m. The dashed lines shows the same RTM applied with the winter-time environ-
Figure 5.2. SFMR modeled brightness temperature ($T_B$) obtained with the geophysical model function (GMF) reported in Sapp (2019) [14] with typical tropical environmental conditions (solid lines) and winter-time extra-tropical conditions (dashed lines). Left: $T_B(WS)$ assuming no rain. Right: $T_B(RR)$ assuming no wind. The colored lines correspond to different frequencies in C-Band from 4.7 GHz to 7.1 GHz, with the higher frequencies corresponding to higher $T_B$.

Environmental conditions in high-latitude regions. The parameters used to characterize the winter environment are: aircraft altitude of 2000 m, SST of 5°C, salinity of 32 psu and $H_r$ of 1000 m. Note that the major difference can be observed in the rain rate dependence. The $T_B(RR)$ in winter conditions increases at a much lower rate compared to the tropical conditions and the spread between the different frequency channels is lesser. In terms of wind speed, the two plots are quite similar, the spread between channels remains unchanged with the main difference being the starting $T_B(WS)$ for low wind speed. This difference is driven by the change in SST.

Moving forward, this chapter presents in a chronological order the thought process through the various hypotheses that were explored and the corresponding results. In this study’s first analysis of the high latitudes winter environment, two distinct
methods are identified and explored to rectify the Radiative Transfer Model (RTM). The reasoning behind the identification of these two methods is based on the ambient temperature. In ETC conditions, the range of ambient temperature variability is quite significant, leading to large variations of the freezing level $H_r$. In this study, two cases are conceived based on the sign of $H_r$.

The first hypothesis focuses on cases where $H_r$ is positive, where it is hypothesized the presence of a melting layer (ML) associated with the rain column, beneath the aircraft that introduces a term of excess attenuation and emission to the overall observed radiative contributions. The second hypothesis looks at cases where $H_r$ is negative, where the freezing conditions of the environment make the possibility of rain null. This hypothesis assigns the excess emission term to a wind driven mixed-phased layer of particles at the surface.
5.1 Excess emission from a melting layer

This first hypothesis suggests that given the lower air temperatures, the freezing level will lie beneath the aircraft, greatly reducing the depth of the rain column, when compared to a typical TC environment. As a result, the SFMR will observe the entire rain column, including the region in the atmosphere where snowflakes or ice crystals melt and transition into raindrops, referred to as the melting layer, freezing level or bright band [38]. Figure 5.3 shows a diagram of the atmospheric layers beneath the aircraft and all the radiative contributions observed by the SFMR with this layout. The intervening atmosphere is divided into three layers: 1.) one below the melting layer (BML) where liquid precipitation is present, 2.) the melting layer (ML) where mixed-phase particles are expected, and 3.) above the melting layer (AML), a precipitation-free layer with only contributions of the atmosphere towards
the overall radiative contributions. The melting layer is known to exhibit enhanced attenuation (and therefore enhanced emission) at microwave frequencies due to the presence of mixed-phase particles that cause the effective dielectric constant of this layer to increase [39]. The attenuation of the melting layer will depend on the size, shape, number and density of the comprised particles. Much of this is currently unknown. With the addition of an intervening melting layer to the RTM, the radiative contributions to the observed $T_B$ are now given by:

- The downwelling cosmic radiation attenuated by the atmosphere and the melting layer reflected by the ocean surface ($T_{\text{cos}}$);
- The downward emission by the atmosphere and the melting layer reflected by the ocean surface ($T_{\text{DOWN}}$);
- The upward emission from the surface attenuated by both the intervening atmosphere and the melting layer ($T_{\text{OCEAN}}$);
- The upwelling emission from the intervening atmosphere, both AML & BML, and the melting layer ($T_{\text{UP}}$).

The modified equations corresponding to the former case are given by:

$$T_{\text{DOWN}} = (1 - \tau_{r,\infty}) \langle T_{r,\infty} \rangle + \tau_{r,\infty} (1 - \tau_{a,\infty}) \langle T_{a,\infty} \rangle + (1 - \tau_{\text{ml}}) \cdot T_{\text{ml}} \rangle$$

$$T_{\text{SKY}} = [T_{\text{DOWN}} + \tau_{r,\infty} \cdot T_{a,\infty} \cdot T_{\text{cos}}] \cdot (1 + \Omega) - (\Omega \cdot T_{\text{cos}})$$

$$T_{\text{UP}} = \tau_{\text{ml}} \cdot (1 - \tau_{r,\infty} \cdot \tau_{a,A/C}) \langle T_{a,A/C} \rangle + \tau_{a,A/C} \cdot (1 - \tau_{\text{ml}}) T_{\text{ml}} + (1 - \tau_{a,A/C}) \langle T_{a,A/C} \rangle$$

$$T_{B} = \tau_{r,\infty} \cdot \tau_{\text{ml}} \cdot \tau_{a,A/C} \cdot (T_{\text{OCEAN}} + (1 - \varepsilon) T_{\text{SKY}}) + T_{\text{UP}}$$

The primary difference from the prior set of equations (Sapp (2019) [14]), reviewed in Chapter 2, is the extra term for the transmissivity and self-emission of the melting
layer. $T_{ml}$ is the physical temperature of the melting layer which is set to 273 K [40]. The transmissivity of the melting layer calculated is given by

$$
\tau_{ml} = e^{-\kappa_r d_c \cdot ml} \tag{5.5}
$$

where $\kappa_r$ is the absorption coefficient for rainfall that exists below the melting layer in Np/m, whose computation is unchanged from the current RTM, $d$ is the melting layer thickness in meters, and $c_{ml}$ is a scaling factor given that the melting layer has enhanced specific attenuation compared to the rain below it.

**Figure 5.4.** Example of modeled C-Band specific attenuation for different effective medium approximations. Figure 9 from *von Lerber, A.* (2015) [39].

Von Lerber(2015) [39] shows an example of modeled specific attenuation in a melting layer at C-Band, displayed in Figure 5.4, where the modeled parameters were constrained by zenith-looking Doppler radar measurements during an event of light rain in Helsinki, Finland, June 26th 2007. This figure shows a melting layer thickness of 300 – 400 m and a specific attenuation in the layer that is approximately 10 times
greater than the rainfall below it. This is used as a guide to model the effect of the melting layer, and the product is specified as \( d \cdot c_{\text{ml}} = 4000 \).

**Figure 5.5.** SFMR modeled brightness temperature \( (T_B) \) obtained with the melting layer (ML) radiative transfer model (RTM) with winter-time extra-tropical conditions. The colored lines correspond to different frequencies in C-Band from 4.7 GHz to 7.1 GHz, with the higher frequencies corresponding to higher \( T_B \).

The estimated freezing level is derived from the flight-level temperature and the assumed lapse rate, unchanged from Klotz(2014) [13]. It is used to place the melting layer and define the depth of any rain column below it, while the thickness of the melting layer is held constant. Through its enhanced attenuation and self-emission, the effect of the melting layer is to amplify the contributions of rain, when present. Thus, the anticipated spreading of brightness temperatures is obtained for much lower rain rates. Figure 5.5 illustrates the modeled \( T_B(WS) \) and \( T_B(RR) \) under the proposed RTM equations. The model output is expected to demonstrate a greater spread of brightness temperatures, particularly at lower rain rates, due to the amplification effect of the melting layer. With regard to wind speed, the melting layer RTM re-
sults in a decrease in the retrieved WS when compared to the current RTM, while maintaining consistency in the spreading between channels.

5.1.1 Results with Melting Layer RTM

The Melting Layer (ML) RTM equations are based on a comprehensive literature review of ground-based radar observations of the melting layer in high latitudes regions. However, its manifestation during the ocean flights had yet to be corroborated. During the NOAA Ocean Winds winter missions 2022, this RTM was implemented on one of the NOAA P-3 aircraft providing a unique opportunity to field-test the model and verify this study’s hypothesis by leveraging other instruments available on the aircraft such as the Imaging Wind and Rain Airborne Profiler (IWRAP), a coherent, conically-scanning, dual-frequency (C-band and Ku-band) radar that measures Doppler velocity and reflectivity profiles from precipitation, as well as ocean surface backscatter [16]. During one of the flights of the 2022 campaign, real-time Ku-Band reflectivity factor showed a layer of enhanced reflectivity at about the estimated height of the freezing level, suggesting the possible existence of a melting layer. Later on, IWRAP Ku-Band data available from prior campaigns is analyzed to evaluate if the observation of a potential melting layer was consistent.

Now, cases where the ML algorithm can be verified are considered. The first example is from the 2012 campaign based out of Saint John (Canada), where both SFMR and IWRAP data were available.

Figure 5.6 shows two plots corresponding to the estimated $H_r$ (red) and the altitude of the aircraft(black), as a function of time since 16:10 UTC from data collected on February 5th 2012(top), and the corresponding SFMR rain rate retrieval comparing the results obtained with the Sapp 2019 RTM [14](black) versus the proposed ML RTM(red)(bottom). From the upper plot, one observes that for this interval of the flight, the estimated $H_r$ remains quite constant within the 500-800m range and
Figure 5.6. Estimated $H_r$ (red) and aircraft altitude (black) in meters for winter flight February 5th 2012 as a function of time in seconds since 16:10 UTC (top). Corresponding SFMR retrieved rain rate (mm/hr) as a function time (in seconds) implementing Sapp 2019 RTM (black) or ML RTM (red) (bottom). The dashed blue lines highlight in time (vertical) and in $H_r$ height (horizontal) where the retrieved rain rate values become highly erratic.

then it drops to negative values. Analyzing the lower plot illustrating the rain rate in mm/hr, the retrieved values obtained with the Sapp 2019 RTM average around 14-20 mm/hr. However, towards the end of the time interval the retrieved values exhibit an abrupt increase, reaching up to 120 mm/hr, which is the retrieval algorithm’s upper limit. One can appreciate that the rain rate retrieval is highly affected by $H_r$, given the rapid deviation in the retrieved values when $H_r$ falls below 200-300m.

The initial segment of the time interval, where $H_r$ sustains a relatively constant magnitude, the retrieved rain rate values do not exhibit a significantly elevated level. Nonetheless, the occurrence of such extended periods of elevated values during a winter storm is unlikely. Analyzing the retrieved rain rate obtained with the proposed
ML RTM (bottom-red), a significant reduction in the values is observed, averaging to approximately 2.7 mm/hr, which may indicate lack of precipitation. Furthermore, the retrievals do not appear to be influenced by rapid fluctuations in $H_r$.

![Figure 5.7](image)

**Figure 5.7.** IWRAP vertical reflectivity profiles in dBZ for four consecutive time intervals of 10 minutes starting at 16:10 UTC. Data from February 5th 2012.

Figure 5.7 shows four plots of a 40 minute time-height cross section beginning at 16:10 UTC, Ku-Band reflectivity factor in dBZ captured with the IWRAP radar conically scanning below the aircraft at 30° incidence at 60 rpm. The plots shown are azimuthally averaged vertical profiles versus time in seconds. It becomes evident by examining the plots that only the third segment displays a discernible enhancement in reflectivity at approximately 500m. Conversely, the rest of the plots do not appear to exhibit any indication of a melting layer, despite the estimated value of $H_r$ suggesting otherwise. Based on these observations, it is apparent that the presence of a melting layer beneath the aircraft is not always certain, even though it may be feasible in
certain scenarios. It is important to note that the IWRAP data does not portray any signs of precipitation, indicating a lack of rain during this segment of the flight.

Figure 5.8. Data from February 3\textsuperscript{rd} 2012. Top: IWRAP vertical reflectivity profile in dBZ as a function of distance in km for a time interval of 10 minutes starting at 18:00 UTC. Middle and bottom plots: Retrieved rain rate (mm/hr) and wind speed (m/s), respectively, as a function of time in seconds for Sapp 2019 RTM (black) and ML RTM (red).
Figure 5.8 presents another example where the possible presence of the melting layer is detected by IWRAP. The figure has three plots: 1.) the top plot depicts the reflectivity factor in dBZ as a function of traveled distance in km, captured with IWRAP, 2.) a plot showing the time interval retrieved rain rate (mm/hr) with Sapp 2019 RTM (black) and ML RTM (red), and 3.) the bottom plot displays the corresponding retrieved wind speed (m/s).

Upon examining the second plot, it is evident that the estimated \( H_r \), denoted by a black line, aligns well with a layer of enhanced reflectivity. This layer starts appearing at the beginning of the time interval and intensifies towards the end ranging 30-40 dBZ. In addition, it is possible to observe the reflectivity signature of rain bands at two distinct points in distance: between 20-30 km and again at 45-55 km, with values below 30 dBZ. This plot provides an excellent depiction of the sporadic nature of rain events in such storms.

Because the freezing level is relatively high in this case, the NOAA 2019 RTM does not retrieve unreasonably high values of rain rate, however, when comparison to the radar reflectivity, it appears the retrieval substantially overestimates the rain rate. Assuming a cool-season Z-R relation \( Z = 130R^2 \), a reflectivity of 30 dBZ corresponds to a rain rate of 3 mm/hr, whereas the estimated rain rates of around 15 mm/hr would correspond to a reflectivity factor of 45 dBZ. It can be observed in the results obtained with ML RTM, that the added radiative contributions due to the assumed presence of a melting layer, serve to reduce the retrieved rain rate. However, it can also be observed that the retrieved rain rate is rather constant, always hovering around 3-6 mm/hr, with only a vague correspondence to the rain structure visible in the radar image. This is the observed result when applying the ML RTM in most cases.

The bottom plot illustrates the obtained wind speeds with each of the RTMs. Although the wind speeds appear relatively similar, the wind speed retrieved with
ML RTM yields lower values. Quantitatively, the calculated bias between the two methods is 1.77 m/s, while the RMSE is 1.81 m/s. Later on this chapter these wind speed values are compared to GPS dropsondes.

A shortcoming of this hypothesis is the requirement of a finite rain rate. That is, there must always be some rain present in order to obtain the effect of a melting layer. It is known, however, that in many flights there was indeed no rain, particularly in below-freezing conditions. Nonetheless, the observed spreading of brightness temperatures exceeds that provided from the current RTM. In scenarios where $H_r$ is positive, albeit marginally so, the probability of precipitation remains negligible owing to the shallowness of the rain column. Thus, it is inferred that the application of the ML RTM is not applicable to all cases within positive $H_r$ values but restricted to circumstances such as $300m < H_r < h$, as this model requires the occurrence of rainfall.
5.2 Excess emission from the surface

This section describes a hypothesis derived from cases where \( H_r \) exhibits negative values, suggesting the absence of rainfall. Despite the rain-free environment, the observed brightness temperatures exceed those provided by the model from Sapp 2019 RTM. In this case, the retrieval algorithm forces \( H_r = 0 \) for any \( H_r \) negative values, which suppresses all radiative contributions from the rain. Consequently, the disagreement between the observed and modeled \( T_B \) values solely impacts the retrieved wind speed, which have been previously reported to not agree with other ground truth sources in the ETC environment [32, 41].

For temperatures below freezing and for low SSTs, it has been reported that as wind speed increases \((WS > 10 \text{m/s})\), sea spray lofted from the sea surface, wave breaking and bursting of bubbles can create a layer of frozen or super-cooled water particles. This layer is referred in this study as a sea-spray surface layer (SL). The large droplets tend to fall out of the spray cloud because of gravity, while the smaller ones remained suspended up to around 100m [42, 43, 44]. The concentration of marine aerosol is reported to increase for sea surface temperatures below 13°C as bubbles rise to the surface slower than in warm waters and have more time to coalesce [45, 46, 47]. The result is a signature resembling a melting layer in SFMR data. In this case, however, the source of the particles is the wind-driven ocean surface, so it is more appropriate parameterize with the wind speed than with a non-existent rain rate.

This sea-spray layer is widely observed in marine icing studies for vessels, structures and marine operations in high latitudes, where this phenomenon poses considerable risk to stability and safety of the crew [48, 49, 50]. The rate of marine icing depends on wind speed, air temperature, sea temperature and the characteristics of the vessel or the structure [49]. This study’s research focus is not the study of the marine icing rate as such but, later on this section, the icing predictor (PPR) is considered as a reference to determine if the existence of a surface layer is plausible in
the studied dates. The PPR is a categorical algorithm frequently used to determine icing potential on vessels based on environmental parameters. It is calculated with the following [51]:

$$PPR = \frac{V_a \cdot (T_f + T_a)}{1 + 0.3 \cdot (T_w - T_f)}$$ (5.6)

where $V_a$ is the wind speed (m/s), $T_f$ is the freezing point of seawater (usually around $-1.7^\circ C$), and $T_w$ is the SST ($^\circ C$) and the PPR units are $m^\circ C/s$. Positive PPR indicates potential icing, and higher PPR values denote higher icing rates.

Considering the established wind speed correlation with marine icing, it was explored whether the difference between observed and modeled brightness temperatures could also be associated with wind speed.

**Figure 5.9.** Left: mean measured $T_B$ in Kelvin (solid lines) and modeled $T_B$ (dashed lines) for five different frequency channels as a function of $U_{ref}$ from January 28th 2014. Higher frequency channels are offset as indicated for clarity. Right: mean $T_B$ difference in Kelvin (measured minus modeled) as a function of $U_{ref}$. Error bars denote ±1 standard deviation of the $T_B$ difference.

### 5.2.1 $T_B$ behavior versus a reference wind speed

In determining the wind speed dependence of the SFMR measurements, an issue arises when determining an independent, or reference, wind speed. In hurricane
research, dropwindsondes are typically employed to provide reference wind speed. However, although a number of dropwindsondes were deployed during winter flights, the quantity available is insufficient to derive a modified wind speed dependence. Instead, this study initially chose to use the SFMR wind speed estimate obtained only from the lowest frequency channel using the Sapp 2019 RTM as a reference wind speed, referred to this wind as $U_{\text{ref}}$. In the absence of rain, one channel is sufficient to obtain a wind speed estimate, and it is expected the lowest frequency channel to be least affected by an intervening surface layer.

Figure 5.9 compares the measured $T_B$ (solid lines) and modeled $T_B$ implementing Sapp 2019 RTM (dashed lines) as a function of $U_{\text{ref}}$ from SFMR observations obtained on 28 January 2014 during a campaign based out of Halifax, Nova Scotia, Canada. The $T_B$s are bin-averaged every 1m/s with respect to $U_{\text{ref}}$. For this day, the mean PPR is around $30m/s$ suggesting moderate presence of marine icing. An increasing discrepancy between measured and modeled brightness temperatures for all channels except for the lowest frequency channel can be observed, which was used as the reference. For the higher frequency channels, the difference between measured and modeled $T_B$ is greater, suggesting the discrepancy is both wind speed and frequency dependent. It would expected that the wind speed differences converge at lower wind speeds where the presence of spray would be diminished. This wind speed-driven discrepancy across the frequency channels has been observed on several dates throughout the available data set.

Based on this evidence, this study hypothesized that the wind-driven sea-spray surface layer is a significant contributor to the observed radiation measured by the SFMR. Figure 5.10 depicts the intervening atmosphere and all relevant radiative contributions with the incorporation of a surface layer. As the sea-spray layer originates from the ocean, one could assign its emissivity to the ocean surface, revising the current ocean excess emissivity model and adjusting it for freezing conditions.
Figure 5.10. Diagram of the proposed surface layer RTM radiative contributions to the total $T_B$ measured by the SFMR.

Alternatively, one may treat the assumed layer separately, characterizing both its self-emission and absorption. It was chosen to implement the latter, using the SFMR data to derive an emissivity model for the surface layer denoted as $\varepsilon_{sl}$.

With reference to Figure 5.10, to account for the effect of the surface layer, the revised equation for $T_B$ is

$$T_B = \tau_{a,A/C} \cdot (T_{OCEAN} + (1 - \varepsilon)T_{SKY}) \cdot \tau_{sl} + T_{UP} + (1 - \tau_{sl})T_{sl}$$

(5.7)

consisting of three terms: 1) the reflected $T_{SKY}$ and upward emission of the ocean ($T_{OCEAN}$) attenuated by the intervening atmosphere (transmissivity $\tau_{a,A/C}$) and by the SL (transmissivity $\tau_{sl}$), 2) $T_{UP}$ calculated with (2.14), and 3) the self-emission of the SL, where $T_{sl}$ is its physical temperature.
To determine the emissivity of the surface layer, a significant challenge due to the absence of any model or available radar observations that characterize this layer arises. However, this study proceeds under the assumption that $U_{ref}$ is accurate. In this scenario, it can be employed the difference between the measured and model brightness temperatures to derive the excess emissivity due to the surface layer. This requires the analysis of all data that meets the criteria of negative $H_r$ values, which assumes a precipitation-free environment. This study refers to the difference between measured $T_B$ and modeled $T_B$ for one frequency channel as the temperature spread $\Delta T_B$:

$$\Delta T_B = T_{B,\text{measured}} - T_{B,\text{model}}$$ \hspace{1cm} (5.8)

where $T_{B,\text{measured}}$ is calculated with (5.7) and $T_{B,\text{model}}$ is obtained with (2.16). The only unknown parameter in (5.7) is the transmissivity of the surface layer $\tau_{sl}$, and it can be isolated through the following:

$$\tau_{sl} = 1 - \frac{\Delta T_B}{T_{sl} - \tau_{a,A/C} \cdot (T_{OCEAN} + (1 - \varepsilon)T_{SKY})}$$ \hspace{1cm} (5.9)

where $\tau_{a,A/C}$, $T_{OCEAN}$, $\varepsilon$ and $T_{SKY}$ are calculated with the formulas specified in Sapp 2019 RTM, reviewed in Chapter 2. This is calculated for all the data that shows a wind speed dependent discrepancy between measured and modeled $T_B$ for negative $H_r$. Consistency has been observed in the spread throughout the data available hence, to derive a general value, after calculating $\tau_{sl}$ for each day individually, the results are averaged. The average value of $\tau_{sl}$ for all available frequency channels is illustrated in Figure 5.11(left). For representation purposes, instead of plotting $\tau_{sl}$, $\varepsilon_{sl} = 1 - \tau_{sl}$ is shown.

It should be noted that the left panel of Figure 5.11 illustrates the emissivity of the surface layer for only four frequency channels. The lowest frequency channel has been used to derive $U_{ref}$, resulting in a zero $\Delta T_B$ and consequently, there is no value for $\varepsilon_{sl}$. 

77
Figure 5.11. Averaged emissivity of SL as a function of wind speed \((U_{ref})\) in m/s. Dashed lines show the linear fit for each of the frequency channels.

Additionally, the second lowest frequency channel, 5.31 GHz, has been excluded from the calculation due to Radio Frequency Interference (RFI) from the IWRAP radar C-Band transmission for certain data sets. In order to maintain consistency across different years, it was decided to omit this channel from the analysis. Its emissivity value can be interpolated from the other frequencies.

A least-square linear polynomial fit is performed over the results to obtain a general value. The lowest frequency channel, 4.74 GHz, does not show a contribution, again because it has been used as the reference. Thus, the estimated emissivities are not absolute, but rather excess to that observed by the 4.74 GHz channel.

Figure 5.12 displays the total sample count as a function of wind speed for the calculated averages of \(\varepsilon_{sl}\). Lack of measurements under 15 m/s is not overly concerning because the wind-generated foam that contributes to the radiative observations by the SFMR is typically not present when wind speeds are below 7-11 m/s. The exact transition point may vary depending on environmental conditions and the RTM version used, but it is close to the established threshold, so the contributions of the layer at those wind speeds is expected to be minimal. Figure 5.13 compares \(T_B(WS)\) obtained with Sapp 2019 RTM (left) and the proposed SL RTM (right). Note that
the SL RTM exhibits a greater spread between frequency channels as the wind speed increases.

**Figure 5.12.** Total count of averaged samples in the emissivity of the surface layer as a function of wind speed in m/s. The vertical blue line denotes the threshold under which the sample count is insufficient.
5.2.2 Results with SL RTM

The SL RTM has been developed based on the assumption that in the absence of rain due to freezing conditions \((H_r < 0m)\), the lowest frequency channel can be used to derive a reference wind speed \((U_{ref})\), given the insufficient availability of independent surface wind speed measurements, to characterize the wind-driven sea-spray surface layer that is thought to contribute in both self-emission and absorption to the overall observed radiative contributions.

Figure 5.14 shows three plots from February 2\(^{nd}\) 2013, based out of Halifax, Nova Scotia, Canada. The top plot depicts the altitude of the aircraft (black) and the estimated value of \(H_r\) (red) plotted against time in seconds since 00:30 UTC. Note that during the selected time interval, \(H_r\) maintains a positive value for a duration
highlighted by the dashed vertical black lines. However, for the remainder of the interval, \( H_r \) is negative.

The middle plot shows the retrieved rain rate (RR) in mm/hr, for the same time interval, using Sapp 2019 RTM (black), SL RTM (red) and ML RTM (cyan) has also been included for comparison purposes. The retrieved rain rate (RR) obtained with Sapp 2019 RTM is only available for the time interval during which \( H_r \) is positive, owing to the retrieval algorithm’s manual setting of the rain rate to zero when \( H_r \) is negative. It is worth noting that the retrieved RR values are highly variable, ranging from 15 mm/hr to 120 mm/hr. As previously mentioned in the prior section, this erratic behavior where the retrieved RR is inversely proportional to \( H_r \) has been observed. Conversely, the SL RTM indicates no rain for the time interval marked by the dashed lines. While the ML RTM reports a constant RR value of approximately 5 mm/hr.

The wind speed retrievals are presented in the bottom plot. Focusing on the time interval indicated by the dashed lines, the SL RTM reports higher wind speed values when compared to those retrieved by the Sapp 2019 and ML RTMs.
Figure 5.14. Data from February 2\textsuperscript{nd} 2013. Top: Aircraft altitude (black) and $H_r$ (red) in meters. Middle: Retrieved rain rate in mm/hr with Sapp 2019 (black), SL (red) and ML (cyan) RTMs. Bottom: Retrieved wind speed in m/s with Sapp 2019 (black), SL (red) and ML (cyan) RTMs. All plots as a function of time in seconds since 00:30 UTC. Black dashed vertical lines denote time interval where $H_r > 0m$. 
Conversely, for the remainder of the time interval, the Sapp 2019 RTM retrieves the highest wind speed values. The ML RTM retrieves the lowest wind speed values for the entire time interval. The overall bias between Sapp 2019 and SL RTM is 1.14 m/s and RMSE 1.45 m/s, and between Sapp 2019 and ML is 4.25 m/s and RMSE 4.47 m/s.

![Figure 5.15. Scatter plot comparing retrieved wind speed with Sapp 2019 RTM against ML RTM (dark blue $H_r > 0 m$, cyan $H_r < 0 m$) and SL RTM (green $H_r > 0 m$, red $H_r < 0 m$) in m/s.](image)

Figure 5.15 displays the wind speed data from Figure 5.14(bottom) in a scatter plot comparing the retrieved wind speed values obtained with the Sapp 2019 RTM to those obtained by the SL and ML RTMs in m/s. The retrievals are color-coded to represent positive values of $H_r$, where green indicates the SL RTM and dark blue represents the ML RTM. Similarly, negative values of $H_r$ are represented by red and cyan for the SL and ML RTMs, respectively.

This data representation allows for a clear observation of the impact of $H_r$ varying from negative to positive on the retrieved data within the same data set. Specifically,
by examining the wind speed values retrieved using the SL RTM (green and red), it can be deduced that when $H_r$ is positive, the SL RTM retrieves slightly higher wind speeds than the Sapp 2019 RTM. However, for negative $H_r$ values, where the contribution of rain is eliminated, the Sapp 2019 RTM retrieves higher wind speeds. Note in this case, that the difference is just an offset due to the linear fit employed to characterize the emissivity of the SL, driven by wind speed.

**Figure 5.16.** Top: Retrieved rain rate with Sapp 2019 RTM (black) and SL RTM (red) as a function of time in seconds. Bottom left: Retrieved wind speed with Sapp 2019 RTM (black), SL RTM (red) and ML RTM (cyan) in m/s. Bottom right: Scatter plot comparing retrieved wind speed in m/s for Sapp 2019 RTM against SL RTM (black) and ML RTM (cyan). All the retrievals have a floor for $H_r$ set at 200m.

The significant discrepancy in the retrieved wind speed values resulting from the algorithm’s automatic deactivation of the rain component when $H_r$ is negative is unrealistic in practical scenarios. To prevent the algorithm from zeroing out the rain portion of the Jacobian matrix in the retrieval algorithm, this study has opted to
modify the minimum value of $H_r$ to 200m, to always allow the algorithm to include contributions of rain. The consequences of implementing this change are shown in Figure 5.16.

The top plot shows the retrieved rain rate that would be obtained with both Sapp 2019 RTM (black) and SL RTM (red) in mm/hr and a $H_r$ floor set at 200m. The retrieval of ML RTM has not been included because it is not affected by this change. Upon analysis, it is observed that the retrieval using Sapp 2019 RTM reports erratically high values of rain rate for the entire time interval. This outcome is attributed to the retrieval algorithm’s observation of $T_B$ difference (spread) between frequency channels. This RTM associates spread with the presence of rain. However, given the relatively shallow depth of the rain column at 200m, a significant amount of rainfall is required to match the modeled brightness temperatures and achieve the observed spread between frequency channels. Conversely, the SL RTM, while it shares the same model as Sapp 2019 RTM for $T_B(RR)$ when no wind present, it introduces a frequency dependence for $T_B(WS)$. Consequently, the SL RTM retrieves very low rain rate values, zero for the most part, because it can assign the spread between channels to higher winds.

The bottom left plot shows the retrieved wind speed. Now, the SL RTM retrieves the highest wind speeds and ML RTM still retrieves lower wind speeds than Sapp 2019 RTM but the bias is smaller. Introducing the $H_r$ floor makes the bias between Sapp 2019 and SL RTMs be -1.61 m/s and between Sapp 2019 and ML RTMs 1.96 m/s. The calculated RMSE are 1.65 m/s for Sapp 2019 and SL RTMs and 2.01 m/s for Sapp 2019 and ML RTMs. The bottom right plot shows the comparison in a scatter plot where black is SL RTM and cyan is ML RTM.
5.2.2.1 Comparison in presence of Rain

Figure 5.17. Data from February 3\textsuperscript{th} 2012. Top: IWRAP vertical reflectivity profile in dBZ as a function of distance in km for a time interval of 10 minutes starting at 18:00 UTC. Middle and bottom plots: Retrieved rain rate (mm/hr) and wind speed (m/s), respectively, as a function of time in seconds for Sapp 2019 RTM (black), SL RTM (red) and ML RTM (cyan).
Despite the SL RTM’s initial development for scenarios where $H_r$ exhibits a negative value, it was decided to investigate its impact on a dataset in which rainfall is present, such as the one examined in the preceding section from February 3\textsuperscript{rd} 2012. In this data set, the reflectivity factor obtained with the IWRAP radar detects three distinct rain columns.

Figure 5.17 shows the reflectivity factor in dBZ measured by the IWRAP radar (top) as a function of distance in km, the retrieved rain rate with Sapp 2019 RTM (black), SL RTM (red) and ML RTM (cyan) in mm/hr (middle) and the retrieved wind speed in m/s (bottom), both retrieval plots as a function of time in seconds. When comparing the reflectivity factor with the rain rate retrieved with the SL RTM, the results exhibit a greater degree of similarity than either the Sapp 2019 RTM, which reports an average rain rate of 15 mm/hr, or the ML RTM, which reports an average rain rate of 5 mm/hr. As for the wind speed, as expected SL RTM retrieves the higher wind speed and ML RTM lower than Sapp 2019 RTM. The bias between Sapp 2019 and SL RTM is -1.81 m/s and the RMSE is 1.82 m/s and between Sapp 2019 and ML RTM is 1.77 m/s and 1.81 m/s, respectively.

The reasons for the apparently superior performance of SL RTM in relation to rain rate in the winter environment are not entirely clear. There are several uncertainties associated with the high latitudes winter-time regions that need to be studied further. One possible explanation is that the wind speed dependence of the brightness temperatures is not independent from frequency, even when $H_r$ is positive.

As a result, a third hypothesis was considered where the current emissivity model of the ocean, rather than an additional unaccounted atmospheric layer, may not be as accurate for this colder environment.
5.3 Wind speed comparisons with GPS dropwindsondes

GPS dropsondes, are instruments deployed from the aircraft to measure temperature, humidity, pressure, and winds between flight level and the surface designed by the National Center for Atmospheric Research (NCAR). The dropsonde moves with the horizontal wind as it falls at 10 m/s (2000 ft/min) and it uses the Global Positioning System (GPS) so that the wind can be determined from the Doppler shifts of the GPS signals. They have been broadly used in hurricane research to study structure and motion, clear-air turbulence associated with upper-level jet structure, and targeted observing strategies for mid-latitude forecasting [10]. During winter missions, the use of dropsondes is not as frequent, resulting in a smaller pool of available data. Despite this limitation, all available data is used to compare against this study’s wind speed retrievals.

The SFMR and the dropsondes have vastly different spatio-temporal resolution and sampling, so this study has followed a two point criteria collocation methodology to pair the results of the SFMR with the dropsondes based on the method described in Polverari(2022) [33]. Pairs of measurements collocated in time and space where the SFMR measurement is obtained within one second of the dropsonde launch time, and where dropsonde’s surface measurement falls within a 10 km radius of the SFMR measurement are considered.

In the following analysis, the reference wind speed, $U_{ref}$, obtained with the lowest frequency channel and assuming rain-free environment, is compared to the estimated neutral surface wind speed at 10m $U_{10N}$ (obtained via interpolation) referred in the figures as $speed_{interp}$. Subsequently, the retrieved wind speed employing different RTMs is also compared to $speed_{interp}$.

Figure 5.18 presents a scatter plot of the 10m neutral wind speed $U_{10N}$ ($speed_{interp}$) against SFMR retrieved $U_{ref}$ in m/s obtained using the Sapp 2019 RTM.
Linear orthogonal regression is used to analyze the results. For $U_{ref}$ obtained with Sapp 2019 RTM, the orthogonal linear fit yields a relationship of $y = 1.18x + 0.58$. This indicates a positive rate of change between $U_{ref}$ and $speed_{interp}$. The average bias is -5.06 m/s and the RMSE is 6.35 m/s. Assuming that the dropsonde measurements are correct, the RTM yields greater wind speed values than the dropsondes.

Recalling that the initial wind speed dependence was derived assuming the 4.74 GHz channel was unaffected by the SL, a scaling factor is applied to the wind excess emissivity ($\varepsilon_{ws}$) from the original RTM, which affects all channels including 4.74 GHz. It is found that a scale factor of 1.38 is necessary to bring the bias of the measurements to zero for Sapp 2019 RTM. Figure 5.19, shows retrieved SFMR $U_{ref}$ values with the scaled $\varepsilon_{ws}$, where now it yields an orthogonal regression of $y = 0.96x + 0.94$ the bias is $\approx 0$ m/s and the RMSE is 3.53 m/s. The scale factor implies an additional emissivity for the 4.74 GHz channel of $(1.38 - 1) \cdot \varepsilon_{ws}$.
Figure 5.19. Scatter plot comparing 10m wind speed \((\text{speed\_interp})\) obtained with GPS dropsondes against retrieved SFMR wind speed with the lowest frequency channel assuming zero rain rate \((U_{\text{ref}})\) in m/s employing Sapp 2019 RTM with a scaling factor of 1.38 applied to \(\varepsilon_{\text{ws}}\). The dashed black lines show the corresponding linear orthogonal regression.

Following the same methodology employed to calculate \(U_{\text{ref}}\) with only the lowest frequency channel and assuming no rain, the process is repeated for the remaining frequency channels to see their behavior. Higher frequencies are recognized to be more susceptible to be affected by rain, however only data from days where the estimated freezing level is below zero so the possibility of rain is null is used. Frequency channel 5.31 GHz has been excluded due to RFI from the IWRAP radar.
Figure 5.20. Scatter plot comparing $U_{10N}$ (speed_interp) from GPS dropsondes against retrieved SFMR wind speed with different reference frequency channel assuming zero rain rate ($U_{ref}$) in m/s. Each row uses a different frequency channel: a-b) 5.57 GHz, c-d) 6.02 GHz, e-f) 6.69 GHz and g-h) 7.09 GHz. SFMR data retrieved with Sapp 2019 RTM unmodified (left) and with scaling factors applied to the surface excess emissivity due to wind speed ($\varepsilon_{ws}$).
Figure 5.20 shows all the scatter plots corresponding to the wind speed comparison in m/s between the ocean surface 10m neutral wind speed $U_{10N}$ (speed interp) against $U_{ref}$, in each row retrieved for a different frequency channel. The left column shows $U_{ref}$ obtained with Sapp 2019 RTM with the linear orthogonal fit of the points in green. The right column shows the scatter plots for $U_{ref}$ values obtained with the same RTM plus a scaling factor to $\varepsilon_{ws}$. This factor is different for each of the frequencies. Table 5.1 summarizes all the linear orthogonal fits, average bias, RMSE and the scaling factors applied to each of the plots in the right column. Upon examination of the results, a trend can be observed regarding the scaling factor of $\varepsilon_{ws}$. It has been noted that a greater scaling factor is required to minimize the average bias between speed interp and $U_{ref}(f)$ for higher frequencies. More precisely, a consistent increment of approximately 5% in the scaling factor from one frequency to another, with the highest frequency displaying the largest scaling factor.

Table 5.1. Calculated linear orthogonal regression (LOR), average bias, RMSE & scaling factor from Figure 5.20.

<table>
<thead>
<tr>
<th>LOR</th>
<th>BIAS (m/s)</th>
<th>RMSE (m/s)</th>
<th>SF</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>y=1.25x-0.68</td>
<td>-5.54</td>
<td>6.70</td>
</tr>
<tr>
<td>b</td>
<td>y=1x-0.21</td>
<td>0.0004</td>
<td>3.48</td>
</tr>
<tr>
<td>c</td>
<td>y=1.23x+0.42</td>
<td>-6.18</td>
<td>7.28</td>
</tr>
<tr>
<td>d</td>
<td>y=1x+0.96</td>
<td>-0.03</td>
<td>3.55</td>
</tr>
<tr>
<td>e</td>
<td>y=1.19x+2.04</td>
<td>-6.89</td>
<td>7.83</td>
</tr>
<tr>
<td>f</td>
<td>y=0.9x+2.49</td>
<td>-0.017</td>
<td>3.43</td>
</tr>
<tr>
<td>g</td>
<td>y=1.18x+2.68</td>
<td>-7.34</td>
<td>8.23</td>
</tr>
<tr>
<td>h</td>
<td>y=0.87x+3.13</td>
<td>-0.02</td>
<td>3.43</td>
</tr>
</tbody>
</table>

Based on the aforementioned findings, it appears that the current emissivity model requires revision to better accommodate the winter environment. However, the estimated required increase in $\varepsilon_{ws}$, especially at higher frequencies, seems high, given that the highest frequency would require a 57% increase of excess emissivity due to wind speed. These results could support the hypothesis of a wind driven sea-spray surface layer given that its composition of mixed-phased water particles would have a
similar attenuation/emission effect to the radiative contributions as rain and therefore higher frequency channels would be more sensitive to it.

Now, the SFMR retrieved wind speeds are compared using all available frequency channels, while varying the RTMs to assess the impact of scaling the emissivity terms or introducing a positive floor to the rain column depth ($H_r$) on the retrievals.

![Figure 5.21](image)

**Figure 5.21.** Scatter plot comparing 10m wind speed ($speed_{interp}$) obtained with GPS dropsondes against SFMR wind speed retrieved with variations of Sapp 2019 RTM: a) original Sapp 2019 RTM, b) Positive rain column depth floor set at 200m ($H_r$), c) $\varepsilon_{ws}$ scaled by 1.38 and $H_r > 200m$ and d) $\varepsilon_{ws}$ scaled by 1.31 and $H_r > 200m$. Dashed lines show the linear orthogonal regression. Units are m/s.

Figure 5.21 presents a set of four scatter plots comparing the SFMR retrieved wind speed against the $speed_{interp}$ with variations of the Sapp 2019 RTM. Panel (a) compares $speed_{interp}$ with the current Sapp 2019 RTM, exhibiting an average bias of -4.22 m/s. By introducing a minimum floor of 200m to the rain column depth
(\(H_r\))(panel b), the bias is reduced by less than 1 m/s. However, if the scaling factor 1.38 is also introduced, increasing the excess emissivity due to wind speed (\(\varepsilon_{ws}\)) by 38% (plot c), then the SFMR retrieves lower wind speed values, suggesting that the scaling factor of \(\varepsilon_{ws}\) may be too large.

To address this, the scaling factor is reduced to 1.31 in panel d, which yields the lowest average bias of 0.06 m/s. Table 5.2 lists the corresponding calculated linear orthogonal regression (LOR), the average bias and the RMSE for each of the plots shown in the figure.

<table>
<thead>
<tr>
<th>LOR</th>
<th>BIAS (m/s)</th>
<th>RMSE (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>y=1.33x-4.24</td>
<td>-4.22</td>
</tr>
<tr>
<td>b</td>
<td>y=1.33x-5.26</td>
<td>-3.53</td>
</tr>
<tr>
<td>c</td>
<td>y=1.05x-2.79</td>
<td>1.43</td>
</tr>
<tr>
<td>d</td>
<td>y=1.11x-2.93</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Table 5.2. Calculated linear orthogonal regression (LOR), average bias & RMSE from Figure 5.21.
Figure 5.22. Scatter plot comparing 10m neutral wind speed (\textit{speed\_interp}) obtained with GPS dropsondes against SFMR wind speed retrieved with SL RTM (black) and ML RTM (cyan) unmodified(left) and with scaling factors applied to the surface excess emissivity due to wind speed ($\varepsilon_{ws}$), 1.31 and 1.138, respectively. Units are m/s.

<table>
<thead>
<tr>
<th>LOR</th>
<th>BIAS (m/s)</th>
<th>RMSE (m/s)</th>
<th>SF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Left SL</td>
<td>y=1.32x-3.99</td>
<td>-4.30</td>
<td>5.72</td>
</tr>
<tr>
<td>Right SL</td>
<td>y=1.09x-2.49</td>
<td>0.007</td>
<td>3.39</td>
</tr>
<tr>
<td>Left ML</td>
<td>y=1.32x-6.28</td>
<td>-2.06</td>
<td>4.35</td>
</tr>
<tr>
<td>Right ML</td>
<td>y=1.22x-5.85</td>
<td>-0.049</td>
<td>3.65</td>
</tr>
</tbody>
</table>

Table 5.3. Calculated linear orthogonal regression (LOR), average bias & RMSE from Figure 5.22.

Now, the wind speed outcomes for the surface layer (SL) RTM and the melting layer (ML) RTM are considered. Figure 5.22(left) shows the scatter plot comparing \textit{speed\_interp} from the GPS dropsondes against the SFMR retrieved wind speed where the SL RTM and ML RTM results are depicted in black and cyan, respectively. As mentioned earlier in this section, the SL RTM produced higher wind speed values than the Sapp 2019 RTM, while the ML RTM yielded lower values. The average bias for SL RTM is greater than Sapp 2019 RTM, at -4.20 m/s whereas the ML RTM demonstrated the lowest bias among the three, measuring at -2.06 m/s.

To address the bias, the scaling factor is reintroduced to increase the excess emissivity due to wind speed ($\varepsilon_{ws}$), as that both the SL and ML RTM employ the Sapp
2019 RTM which was previously adjusted by modifying $\varepsilon_{ws}$. Figure 5.22(right) displays the results of increasing $\varepsilon_{ws}$ by 31% for the SL RTM and 13.8% for the ML RTM, reducing the average bias to 0.007 m/s and -0.049 m/s, respectively.

**Figure 5.23.** Data from February 3rd 2012. Retrieved rain rate (RR) in mm/hr as a function of time in seconds for Sapp 2019 RTM (black), ML RTM (cyan) and SL RTM (red). Solid lines correspond to RR retrieved with a scaling factor applied to $\varepsilon_{ws}$ for Sapp 2019, ML and SL RTMs. Dashed lines show RR without the scaling factor in the RTMs.

The scaling of $\varepsilon_{ws}$ for the winter environment may be justified due to the extended lifetime of foam on the sea surface in cold temperatures. Miyake and Abe [52] and Wu [53] proposed a relation for the lifetime of foam as:

$$L = e^{-T_w/25}$$  \hspace{1cm} (5.10)

where $L$ is the lifetime and $T_w$ is water temperature in Celsius. Though enhanced lifetime of foam is plausible, it is not proven in this case. There are mixed reports as to the prevalence of whitecap coverage with temperature, though there are reports
of notable decrease in whitecap coverage for sea surface temperatures above 20°C, which incorporates nearly all hurricane conditions.

To conclude this section, the impact of introducing the corresponding scaling factors of the ocean surface emissivity to all the RTMs on the rain rate retrievals is examined. Figure 5.23 illustrates the SFMR-retrieved rain rate in mm/hr using the Sapp 2019 (black), ML (cyan), and SL (red) radiative transfer models. The dashed lines represent the retrieved rain rate obtained with the RTMs without the scaling factor.

It is worth noting that for the Sapp 2019 and ML RTMs, although the scaling factor reduces the wind speed bias when comparing the data to the GPS dropsondes, it has little effect on the retrieved rain rate. In contrast, the most affected RTM is the surface layer one, for which applying the scaling factor to $\varepsilon_{ws}$ results in an increase of 4.8 mm/hr in the retrieved rain rate.
CHAPTER 6
CONCLUSIONS

In this dissertation, the capabilities and limitations of the Stepped Frequency Microwave Radiometer (SFMR) in estimating ocean surface wind speed and rain rate in extra-tropical cyclones (ETC) were explored. The SFMR has been extensively used by hurricane specialists for issuing watches and warnings, as well as for post-storm studies and satellite calibrations.

This study has focused on improving the accuracy and reliability of SFMR measurements in high-latitude regions during winter time, where the retrieval algorithm yields inaccurately elevated rain rates and potentially overestimates the wind speed. By examining the effects of environmental factors such as, air temperature, sea surface temperature, sea spray and rain on the observed brightness temperature ($T_B$) over a range of six C-band frequencies, this study has developed potential solutions to address the aforementioned issue.

The University of Massachusetts Amherst Microwave Remote Sensing Laboratory (MIRSL) developed a specialized version of the SFMR called UMass Simultaneous Frequency Microwave Radiometer (USFMR) that operates six frequency channels simultaneously. Currently, the SFMR requires an average time of 5-10 seconds of averaging to cycle through the six different frequency channels, so in regions with strong wind/rain gradients such as the eye wall of a hurricane, finer scale details can be overlooked. Conversely, the USFMR eliminates the averaging time obtaining a new independent sample every second. As part of this dissertation, the performance of the SFMR sampling sequentially versus the USFMR sampling simultaneously was
assessed with data collected during the 2019 hurricane season, where the USFMR was installed alongside the operational SFMR on board one of the NOAA WP-3D aircrafts. This dissertation provides comprehensive documentation of all hardware and software modifications made to the USFMR system.

The following sections present detailed conclusions from Chapters 3, 4, and 5, as well as future work suggestions.

6.1 Summary of USFMR system updates

Several updates have been implemented on the USFMR (UMass Simultaneous Frequency Microwave Radiometer) instrument, with the intention of bringing the system up to date and ready for future deployment. The original embedded system encompassed a PC104 embedded computer operating on the Windows95 platform. This computer system was equipped with a microprocessor, an analog-to-digital (A/D) converter, and a field-programmable gate array (FPGA) responsible for generating all essential control signals required by the system.

The instrument now employs a Raspberry Pi serving as the embedded computer, running a Linux operating system. Raspberry Pi expansion board is used as the A/D converter (ADS1256), and a custom made expansion board houses the temperature control system employing digital temperature sensors. Control signals are generated by an FPGA (tinyFPGA) that works in conjunction with the Raspberry Pi.

A redesign of the integrator board was necessary after the failure of the original board. The original board, the synchronous detector circuit (SDC) was divided between the top and bottom layers, this division resulted in inconveniences when troubleshooting the board. In the new design, all components of the SDC have been consolidated onto the top layer of the board, making troubleshooting procedures easier.
The software architecture of the system is implemented in the C programming language. It comprises two distinct components: the instrument code responsible for raw data collection, and the user’s computer code which facilitates data retrieval from the instrument and supports near real-time processing, if required. The instrument code is specifically designed to operate within the instrument itself, enabling efficient collection of raw data and storing it in the Raspberry Pi memory card. The user’s computer code serves as an interface for accessing the instrument’s data, facilitating its retrieval and subsequent processing.

Multiple calibration procedures were described in this chapter. Calibration ensures the accuracy and reliability of the instrument’s measurements. Given the high sensitivity of radiometers and potential changes that may occur during storage or transportation, repeating the calibration procedures becomes essential. By doing so, any potential discrepancies or deviations can be identified and rectified, thereby guaranteeing optimal performance of the instrument upon redeployment.

6.2 SFMR & USFMR sampling methodology performance analysis

In this chapter, a comparison was made between data obtained from the operational Stepped Frequency Microwave Radiometer (SFMR) with that of the UMass Simultaneous Frequency Microwave Radiometer (USFMR). The data was collected aboard one of the NOAA P-3 aircrafts during hurricane Lorenzo, which occurred in the 2019 hurricane season.

The primary objective of this experiment was to evaluate the performance between the SFMR and USFMR instruments, given their distinct sampling methodologies, sequential and simultaneous, respectively.

While both instruments take brightness temperature measurements of the ocean surface at six different C-band frequencies, the SFMR steps through them individu-
ally, requiring roughly 10 seconds to complete a full independent measurement. Conversely, the USFMR samples of the frequencies simultaneously, obtaining a complete, independent measurement every second.

The research findings revealed that while the measurements obtained from both instruments were similar, notable distinctions were observed. Specifically, the USFMR instrument demonstrated a higher degree of fidelity in capturing finer-scale details, whereas the SFMR instrument tended to provide a smoother representation of the surveyed area. In-depth examination of the variance spectrum of the retrieved data corroborated these observations. It was determined that the USFMR measurements displayed higher levels of energy in the higher frequencies, further affirming the presence of finer details within the USFMR data compared to the SFMR data.

During the analysis of the USFMR data, an issue was identified where a deviation from the SFMR measurements was observed, particularly during the early phase of the hurricane flight. Further investigation revealed that this discrepancy was attributable to a temperature-related factor. It was determined that the USFMR instrument experienced difficulties when confronted with abrupt temperature changes. The instrument enclosure needs a consistent temperature environment; however, the existing heating system exhibited inadequate performance in rapidly restoring the optimal temperature following altitude-induced fluctuations in the flight-level air temperature.

Given the constant monitoring of the instrument’s temperature, it is possible to eliminate the bias associated with temperature variations through post-processing techniques. However, to facilitate real-time display of the retrieved data, it becomes imperative to update the temperature control system to one capable of promptly responding to changes in temperature.
6.3 Refinement of the radiative transfer model for winter-time retrievals

In this Chapter, it is considered the radiative transfer model (RTM) employed by the Stepped Frequency Microwave Radiometer (SFMR) and its application in airborne winter time observations of high-latitude storms and extra tropical cyclones. The current RTM described in Sapp (2019) [14], developed and tuned for use in tropical cyclones (TCs), is found to not model adequately the observed brightness temperatures typically encountered in these cold conditions. While the brightness temperatures observed at several frequencies across C-band are lower, they are more spread apart from each other than the TC RTM predicts.

Initially, this study considered two hypotheses to explain the differences between the measured and modeled $T_B$ based on the estimated rain column depth ($H_r$), deduced from the flight-level temperature and an assumed lapse rate. One hypothesis, for positive $H_r$ values, assumed the presence of a melting layer between the aircraft and the surface. This melting layer imparts enhanced attenuation and emission, which results in increased spreading of the brightness temperatures. The properties of the melting layer scale with rain rate, as determined through Doppler radar measurements from von Lerber (2015) [39]. New radiative transfer model equations were generated to incorporate the melting layer contributions to the RTM equations.

These new equations were tested as the official running algorithm for the SFMR flying aboard the NOAA P-3 aircraft during the 2022 ocean winds winter campaign in Alaska, USA. The proposed retrieval transfer model (RTM) equations exhibit a notable increase in the spread of brightness temperatures associated with lower precipitation intensities, thereby effectively reducing the estimated rain rates. The retrieved wind speed is also found to be reduced by the ML RTM.

During a few of the campaigns, reflectivity factor measurements of a possible melting layer were obtained with the Imaging Wind and Rain Airborne Profiler (IWRAP)
radar, also installed on the aircraft. Upon recognizing the potential of the IWRAP radar to detect the possible signature of the melting layer beneath the aircraft, data from past winter missions was used to assess the consistency of the melting layer presence. This study’s findings indicate that the presence of the melting layer, even in suitable atmospheric conditions for its existence, is not always guaranteed. While the retrievals obtained with the ML RTM appear to yield favorable outcomes with respect to rain rate, it is important to acknowledge that these results may not necessarily reflect the actual values of wind speed and rain rate given that the algorithm achieves these results by considering a constant presence of a melting layer.

A second hypothesis posits the existence of a wind-dependent excess emissivity, which may be attributed to the presence of a surface-based layer of mixed-phase droplets lofted from the surface. This phenomenon has been reported in marine icing studies, however, there is a lack of characterization of this layer in the literature. For freezing conditions, where $H_r$ is negative and hence the existence of rain should be null, the measured brightness temperature exhibits a frequency and wind speed dependent difference from the predicted $T_B$. This difference is used to characterize the radiative contributions of a possible sea-spray layer and adjust the RTM equations accordingly. To do so, it is required to have an independent, or reference surface wind speed measurement to characterize the layer. Given the insufficient availability of GPS dropsondes in the winter flights, a reference wind speed ($U_{ref}$) is derived assuming no rain and only using the brightness temperature measured by the lowest frequency channel.

This second hypothesis is most consistent with observations when the freezing level, is at or below the surface. It is found that the latter hypothesis appears to represent the precipitation observations better than the first, even when $H_r$ is positive, in large part because there is often little to no rain present in the observations. IWRAP data has been utilized to determine presence of rainfall and subsequently
compared to the retrieved values of the SFMR. The SL RTM retrieves higher wind speed values.

It was also observed that in cases where $H_r$ exhibited oscillations between positive and negative values, a distinct separation became evident in the retrieved wind speed owing to the current RTM switching on and off the rain contribution. In order to address this issue, a corrective measure was implemented by introducing a fixed floor to $H_r$, setting a minimum allowable value of 200 meters. This adjustment ensures a consistent inclusion of a minimal rain contribution in the retrievals, mitigating the previously observed anomalies.

Within the context of this study, a third hypothesis emerged, considering that the ocean surface emissivity model is potentially not representing conditions accurately. In the subsequent section of this chapter, the Sapp 2019 Radiative Transfer Model (RTM), the ML RTM and the SL RTM to observations obtained from GPS dropsondes were compared, assuming their measurements can be trusted.

The analysis showed that all RTMs substantially overestimate the wind speed compared to the GPS dropsondes measurements. In order to correct the bias, it was found that the RTMs derived from Sapp 2019 RTM, required a scaling factor to increase the excess emissivity of the ocean due to wind speed. A possible reason for this is the extended lifetime of foam on the sea surface as temperature decreases.

Upon incorporating the scaling factors into the RTM, the analysis revealed that the Sapp 2019 RTM exhibited a reduction in wind speed. However, despite this implementation, the issue of inconsistent rain rate retrieval persisted. In contrast, the newly proposed RTMs, namely the ML and the SL RTMs, demonstrated promising outcomes after the application of the scaling factor in both wind speed and rain rate. However, the ML RTM consistently retrieved rain rates in the range of 2-5 mm/hr, with no instances of retrieving zero rainfall. Conversely, the SL RTM was capable of retrieving zero rain rate; however, a comparison against the reflectivity
factor obtained with IWRAP suggests a potential tendency to still overestimate the actual rain rate.

The scaling factor applied to the emissivity of the ocean was determined assuming that the GPS dropsondes measurements of surface wind speed were accurate. However, there remains uncertainty regarding the validity of these measurements, particularly under winter-time conditions. During such periods, factors such as wave sheltering effect and the saturation of humidity profiles caused by sea spray may potentially influence the accuracy of wind speed measurements. Neutral atmospheric stability conditions are assumed with a logarithmic profile of the wind when calculating $U_{10N}$. This condition is not always met.

Further investigation is required to establish a final radiative transfer model that properly characterizes the atmospheric conditions in extra-tropical cyclones and the air-sea interaction for low temperatures. The lack of independent and trusted surface observations in winter time limits the possibilities to properly derive a model. Subsequent actions could involve the deployment of a larger number of GPS dropsondes during winter missions as well as using satellite data from instruments such as the Advanced Scatterometer (ASCAT), to obtain 10-m neutral surface wind speed. Although it would require performing temporal averages of the SFMR data given the difference in spatial scales, and also taking into account that ASCAT is been reported to display reduced sensitivity for wind speeds above 35 m/s [54]. Back in 2021 a novel NOAA-saildrone project deployed five unmanned saildrones during hurricane Sam to directly measure ocean surface wind speed with ultrasonic anemometers, air temperature, relative humidity, significant wave height, sea surface temperature and many other parameters [55, 56, 57]. Acquiring such type of data directly from the ocean surface would greatly benefit this research, considering the inherent challenges associated with obtaining reliable information in such proximity to the ocean surface at present.
This appendix shows the logic diagrams designed for the FPGA to translate the control signal from the Raspberry Pi to selected the SFMR mode control signals for the 4-port switch. Truth table can be found in section 3.1.2 (Table 3.5).

**Figure 7.1.** Logic diagram for Horizontal port selection in the tinyFPGA (truth Table (3.5))
The following table shows what is the output of the MUX 4:1 given S1 and S2.

<table>
<thead>
<tr>
<th>S1</th>
<th>S2</th>
<th>OUT</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>Pulse</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Reverse Pulse</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

SEL1 AND SEL2 GENERATOR FOR V SIGNAL

Figure 7.2. Logic diagram for Vertical port selection in the tinyFPGA (truth table (3.5)).

Figure 7.3. Logic diagram for Reference port selection in the tinyFPGA (truth table (3.5)).
Figure 7.4. Logic diagram for Calibration (noise source) port selection in the tinyF-PGA (truth table (3.5)).
Figure 8.1. Integrator board layout designed with Altium: PCB design and Software tools.

The following pages show the schematics from the PCB design in Altium.
In section 5.3, wind speed comparisons with GPS dropsondes against the retrieved wind speed with the latest update of the RTM (Sapp (2019)) were done. This appendix shows the results of wind speed comparisons implementing the prior RTM, described in Klotz (2014) [13].

![Figure 9.1](image)

**Figure 9.1.** Scatter plot comparing 10m neutral wind speed $U_{10N}$ (speed_interp) obtained with GPS dropsondes against retrieved SFMR wind speed with the lowest frequency channel assuming zero rain rate ($U_{ref}$) in m/s. Black and cyan dots show SFMR data retrieved with Sapp 2019 RTM and Klotz 2014 RTM, respectively. Dashed lines show the linear orthogonal regression of the data.

Figure 9.1 presents a scatter plot of $U_{10N}$ against SFMR $U_{ref}$ retrieved with Sapp 2019 RTM (black) and Klotz 2014 (cyan). Both RTMs overestimate the wind speed
compared to the GPS dropsondes, however, while Sapp 2019 RTM exhibits a positive
slope and the bias increases with wind speed, whereas the Klotz 2014 RTM displays
more of an offset, suggesting a consistent deviation from the observed wind speed
values. The statistical values for Sapp 2019 RTM are already shown in section 5.3.

$U_{ref}$ obtained with Klotz 2014 results in an orthogonal regression of $y = 0.88x +
4.79$, with the primary focus being on the deviation represented by the y-intercept.
The average bias is lesser than Sapp 2019 RTM being at -1.84 m/s and an RMSE of
3.91 m/s.

Given that the difference between $U_{10N}$ and $U_{ref}$ obtained with Klotz 2014 RTM is
hardly wind-dependent, the bias was sought to be addressed through an adjustment of
the specular term of the surface emissivity ($\varepsilon_0$). Specifically, a scaling factor of 1.0195
was found to be effective in bringing the bias down to zero. As illustrated in Figure
5.19(right), the resulting scatter plot demonstrates the impact of applying the scaling
factor to $\varepsilon_0$. Notably, the orthogonal regression now corresponds to $y = 0.97x + 0.69$,
the bias is $\approx 0$ m/s , and the RMSE is equal to 3.78 m/s.

<table>
<thead>
<tr>
<th>LOR</th>
<th>BIAS (m/s)</th>
<th>RMSE (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a $y=1.01x+0.82$</td>
<td>-1.21</td>
<td>3.54</td>
</tr>
<tr>
<td>b $y=1.02x+0.21$</td>
<td>-0.88</td>
<td>3.36</td>
</tr>
<tr>
<td>c $y=1.07x-2.88$</td>
<td>0.97</td>
<td>3.50</td>
</tr>
<tr>
<td>d $y=1.07x-2.11$</td>
<td>0.05</td>
<td>3.32</td>
</tr>
</tbody>
</table>

Table 9.1. Calculated linear orthogonal regression (LOR), average bias & RMSE from Figure 9.2.

The scatter plots comparing the results obtained with Klotz 2014 RTM are pre-
sented in Figure 9.2. It is observed that the average bias generated by Klotz 2014
RTM, without any modifications, is -1.21 m/s. This value is significantly lower than
the bias introduced by Sapp 2019 RTM. If the rain column depth threshold is imple-
mented at 200m, the bias decreases to -0.88 m/s (plot b). Additionally, if the scaling
Figure 9.2. Scatter plot comparing 10m wind speed (speed_interp) obtained with GPS drop sondes against SFMR wind speed retrieved with variations of Klotz 2014 RTM: a) original Klotz RTM, b) Positive rain column depth floor set at 200m ($H_r$), c) $\varepsilon_0$ scaled by 1.0195 and $H_r > 200m$ and d) $\varepsilon_0$ scaled by 1.0095 and $H_r > 200m$. Dashed lines show the linear orthogonal regression. Units are m/s.

A factor of 1.0195 is applied to the specular emissivity ($\varepsilon_0$), the bias increases to 0.97 m/s, suggesting that the scaling factor may be too large (plot c).

The outcome of decreasing the scaling factor to 1.0095 is illustrated in Figure 9.2(d), yielding an average bias of 0.053 m/s.

To conclude the analysis, the impact of increasing the smooth emissivity of the ocean surface to the retrieved rain rate with Klotz 2014 RTM was examined. Figure 9.3 illustrates the SFMR retrieved rain rate in mm/hr using this RTM. The dashed line represents the rain rate retrieved without the scaling factor to the smooth ocean surface emissivity. Note that, similarly to Sapp 2019 RTM, although the scaling factor reduces the wind speed, it has little effect to the rain rate.
Figure 9.3. Data from February 3rd 2012. Retrieved rain rate (RR) in mm/hr as a function of time in seconds for Klotz 2014 RTM. Solid lines correspond to RR retrieved with a scaling factor applied to $\varepsilon_0$. Dashed lines show RR without the scaling factor in the RTM.
BIBLIOGRAPHY


